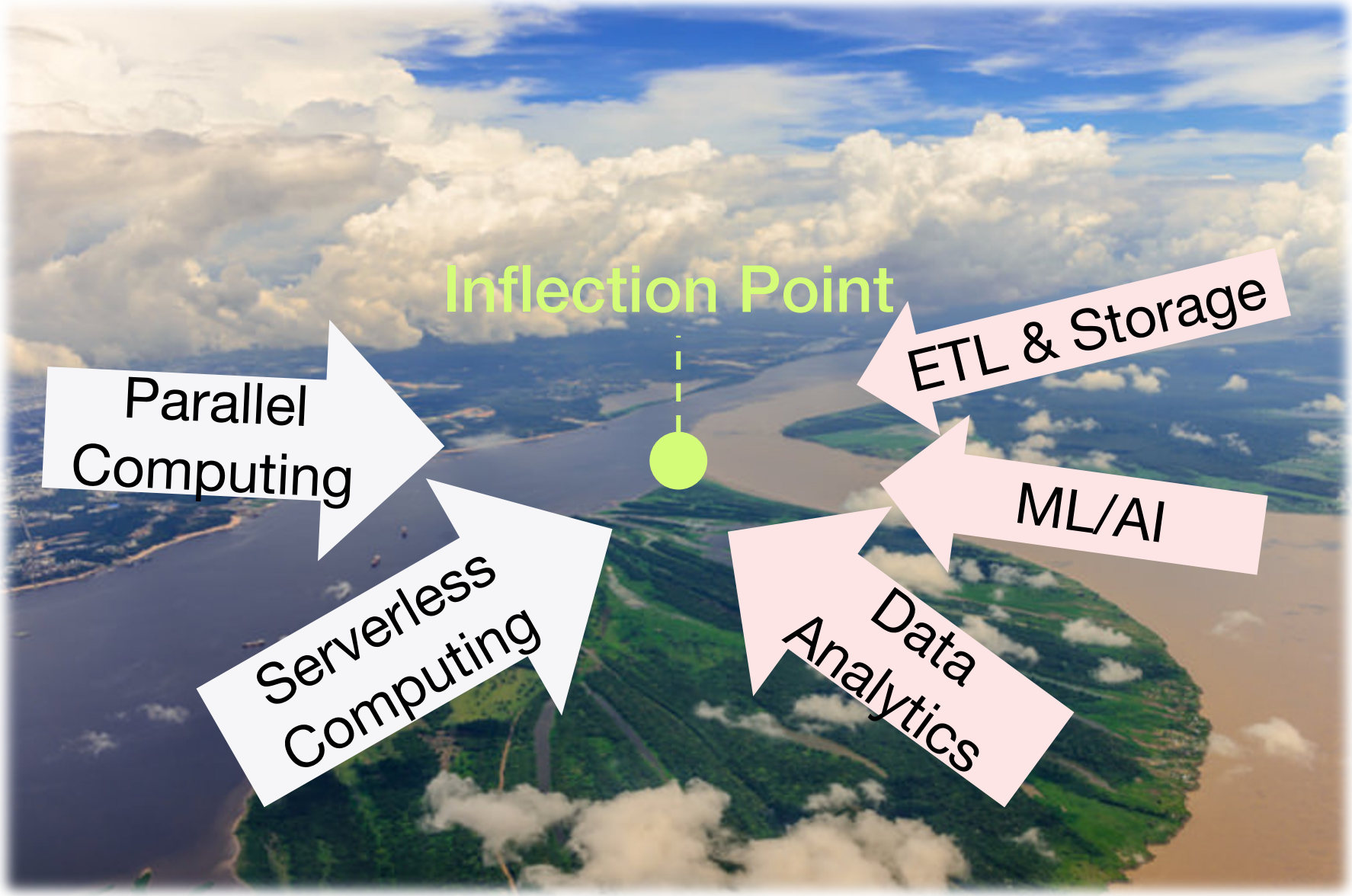
Serverless Parallel Computing

DS 5110: Big Data Systems (Spring 2023)

Lecture 7b

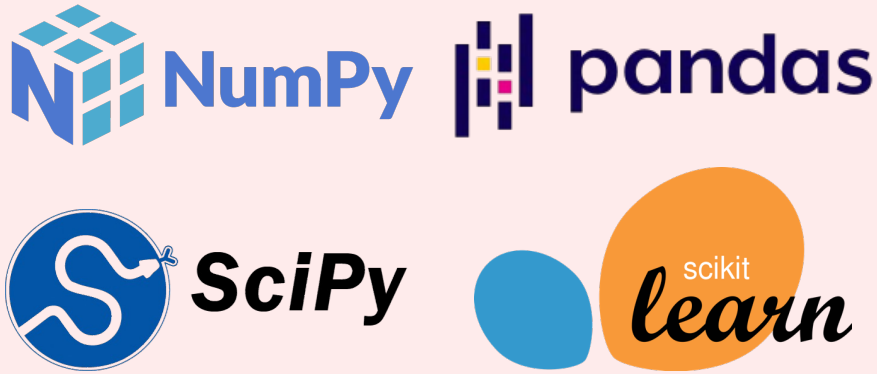
Yue Cheng

Confluence: When stateful apps meet serverless computing



Today's data analytics landscape

Libraries efficient for O(1MB)



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Libraries efficient for O(1MB)

Frameworks for O(100s GB)

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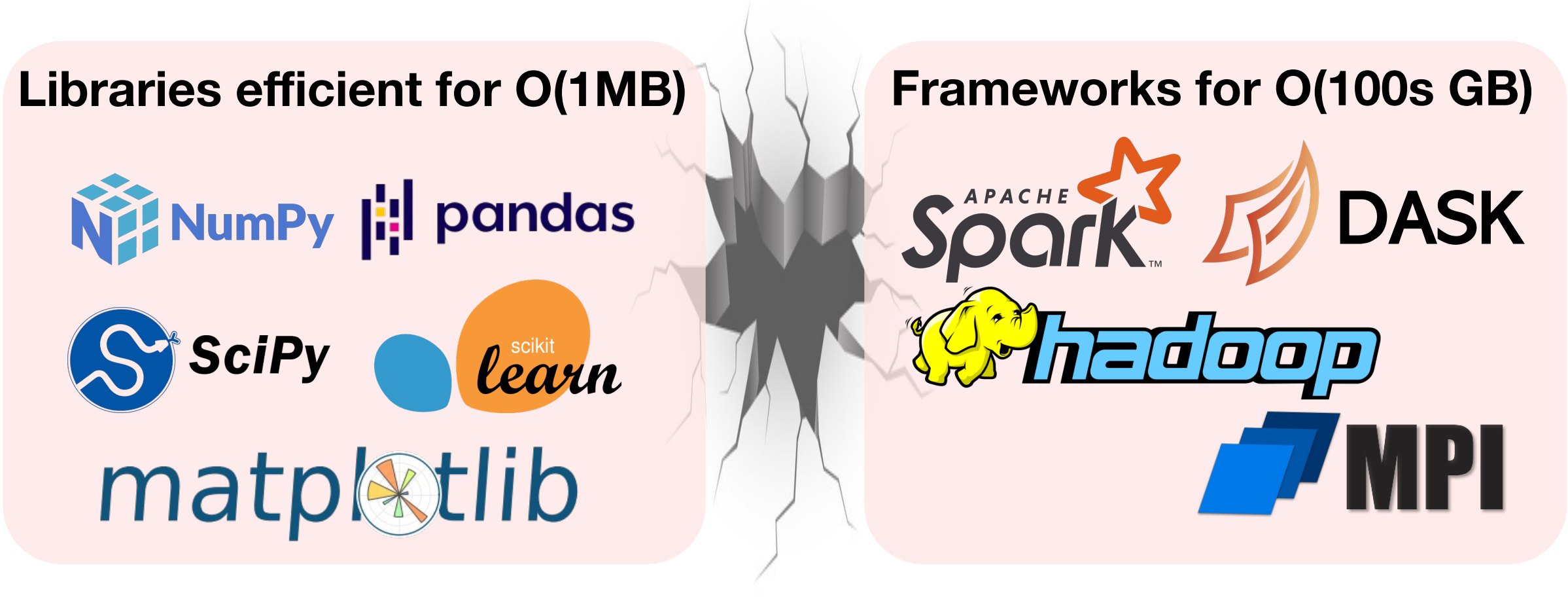


Today's data analytics landscape

Libraries efficient for O(1MB)

- Easy to program (writing centralized code)
- Low barrier for environment setup (just installing libs)
- Well understood

- No scalability / elasticity
- Not able to efficiently handle large data

Frameworks for O(100s GB)

- Scale to 100s GB data

- Difficult to program and debug
  - Requires distributed systems knowledge
- No elasticity
- High barrier for environment setup
  - Requires low-level administration skills

Today's data analytics landscape

Libraries efficient for O(1MB)

Easy-to-use but not scalable nor elastic

Frameworks for O(100s GB)

Scalable but not easy-to-use nor elastic

Making a strong case for

Running elastic, pay-per-use stateful apps on Serverless

Libraries efficient for O(1MB)

Frameworks for O(100s GB)

Easy-to-use

Elastic

Pay-per-use

Scalable

Recap: Serverless computing

Recap: Serverless computing

Car analogy

Own a car

(Bare metal servers)

Rent a car

(VPS)

City car-sharing

(Serverless)

Cars are parked **95%** of the time (loige.link/car-parked-95)

How much do you use the car?

Recap: What is serverless computing?

Many people define it many ways

A programming abstraction that enables users to upload programs, run them at **virtually** any scale, and pay **only for the resources used**

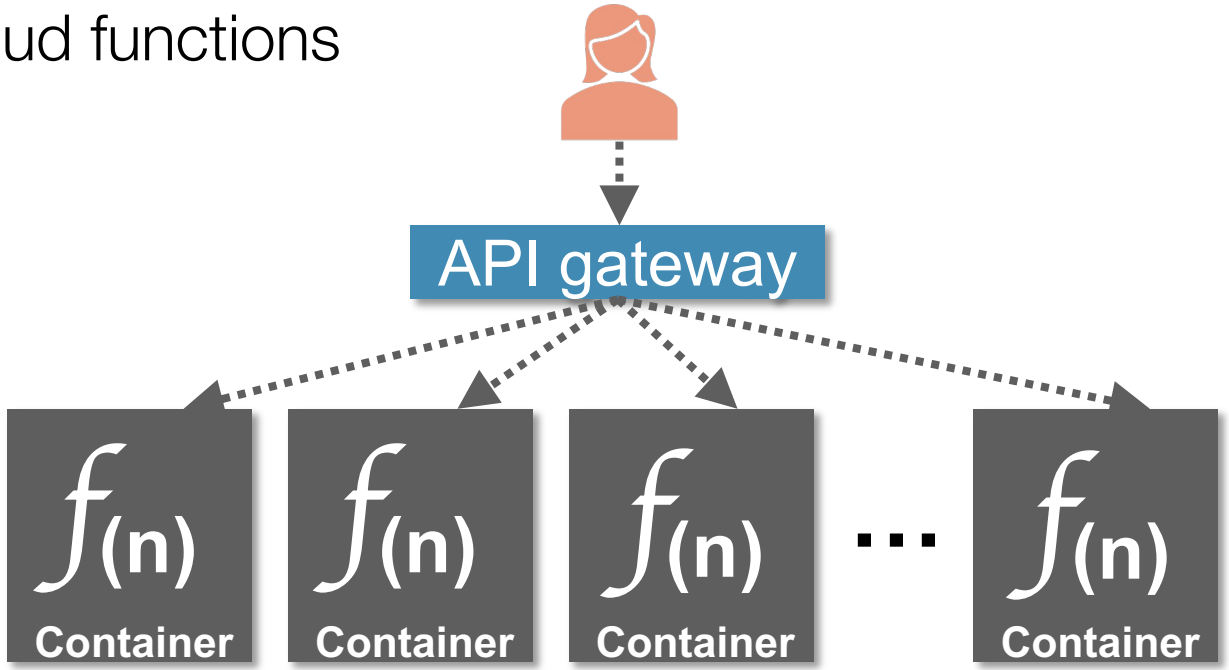
- **Function-as-a-Service (FaaS):** Cloud functions as a basic deployment unit

AWS Lambda

Azure Functions

Google Cloud Functions

Alibaba Function Compute

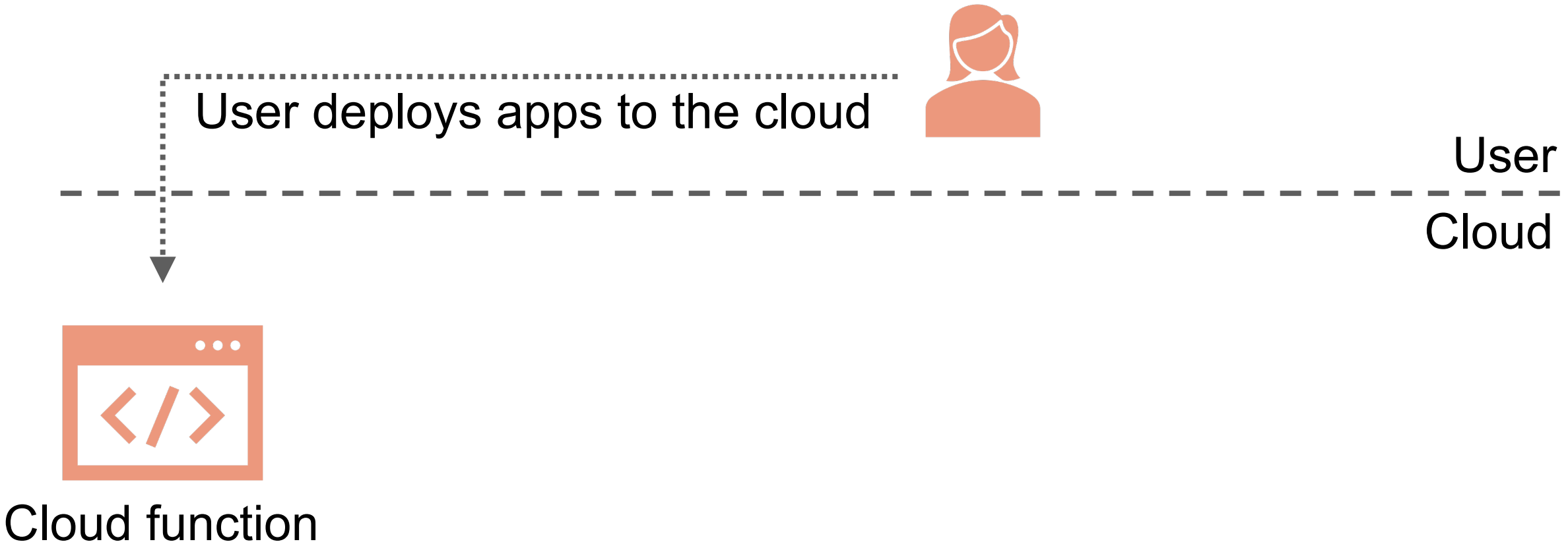


Function-as-a-Service (FaaS)

User

Cloud

Function-as-a-Service (FaaS)



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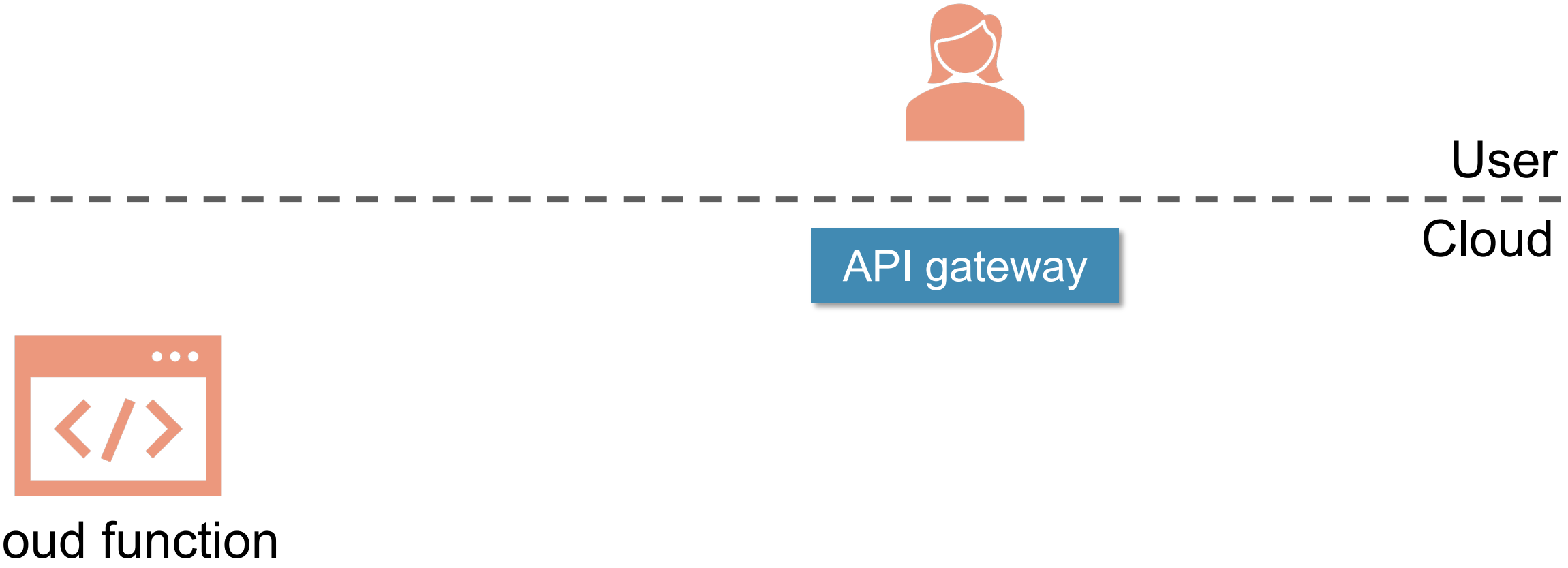

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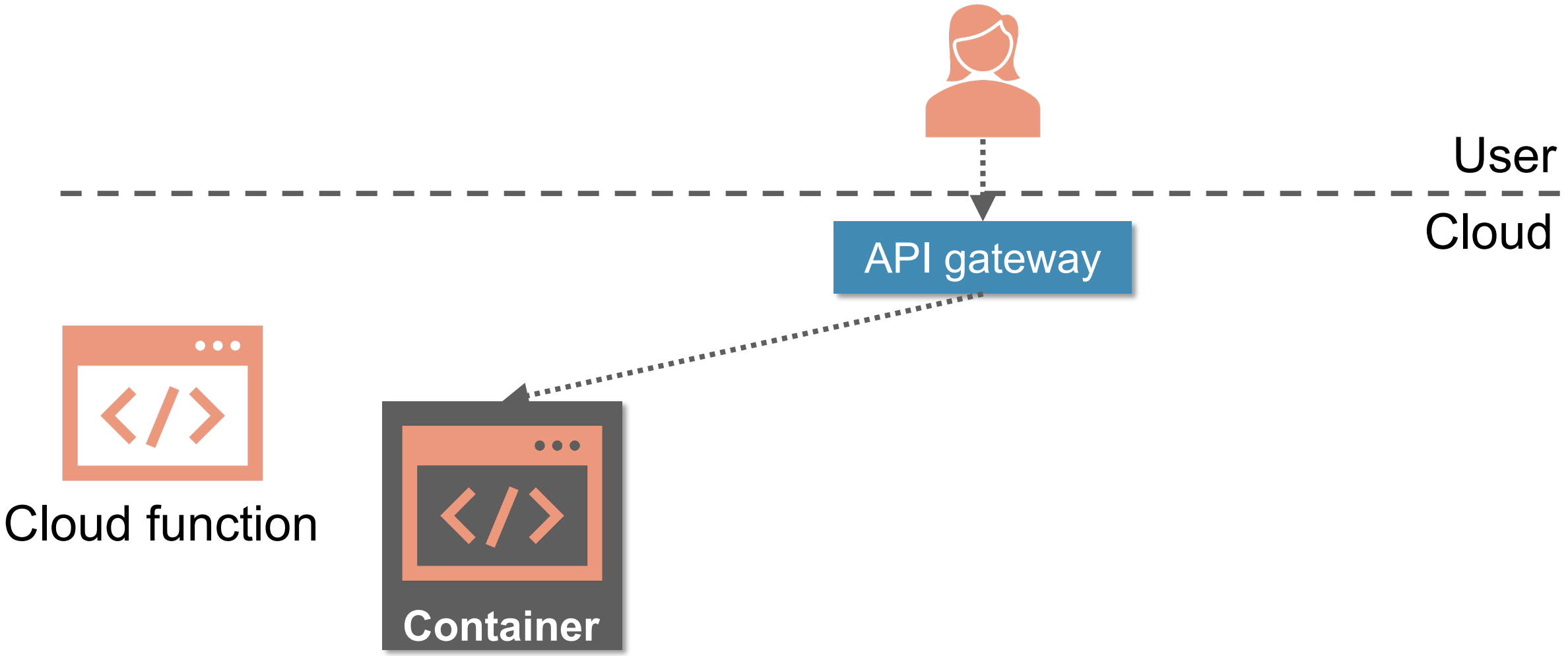

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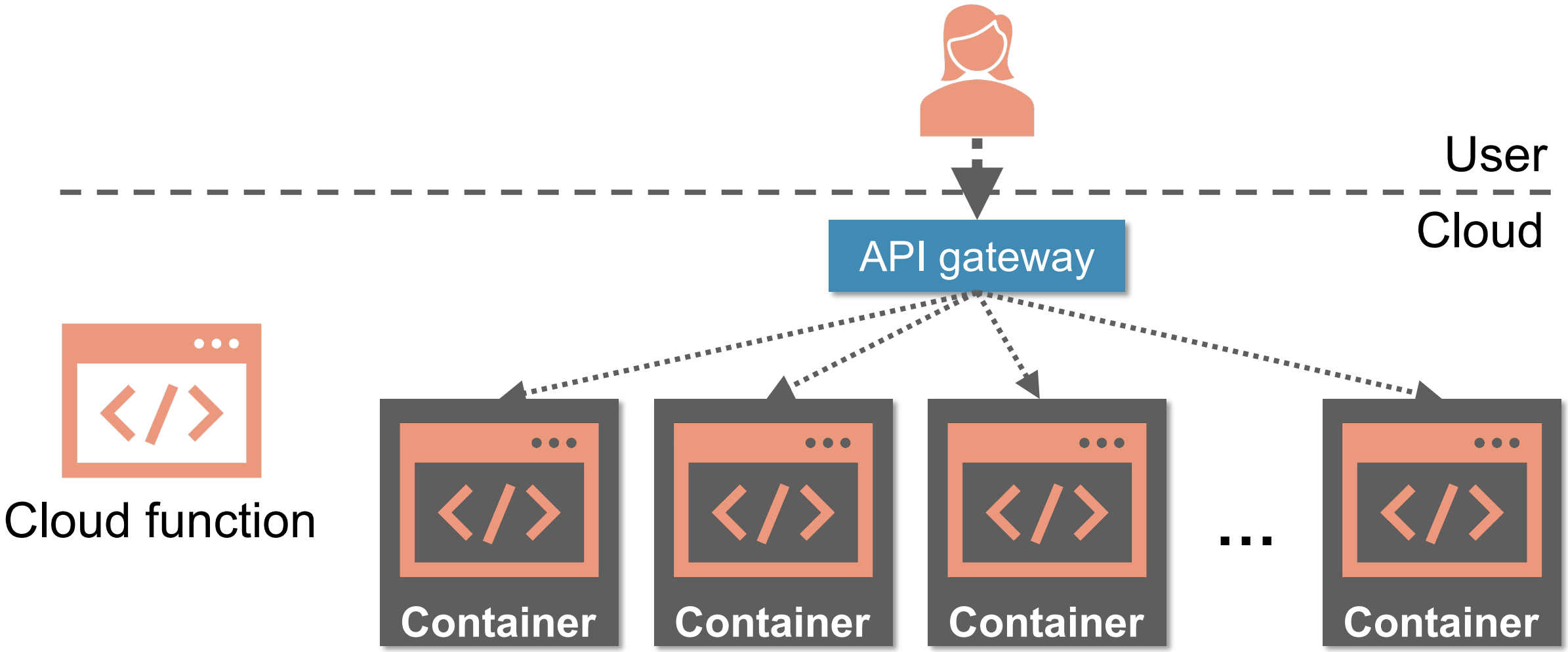

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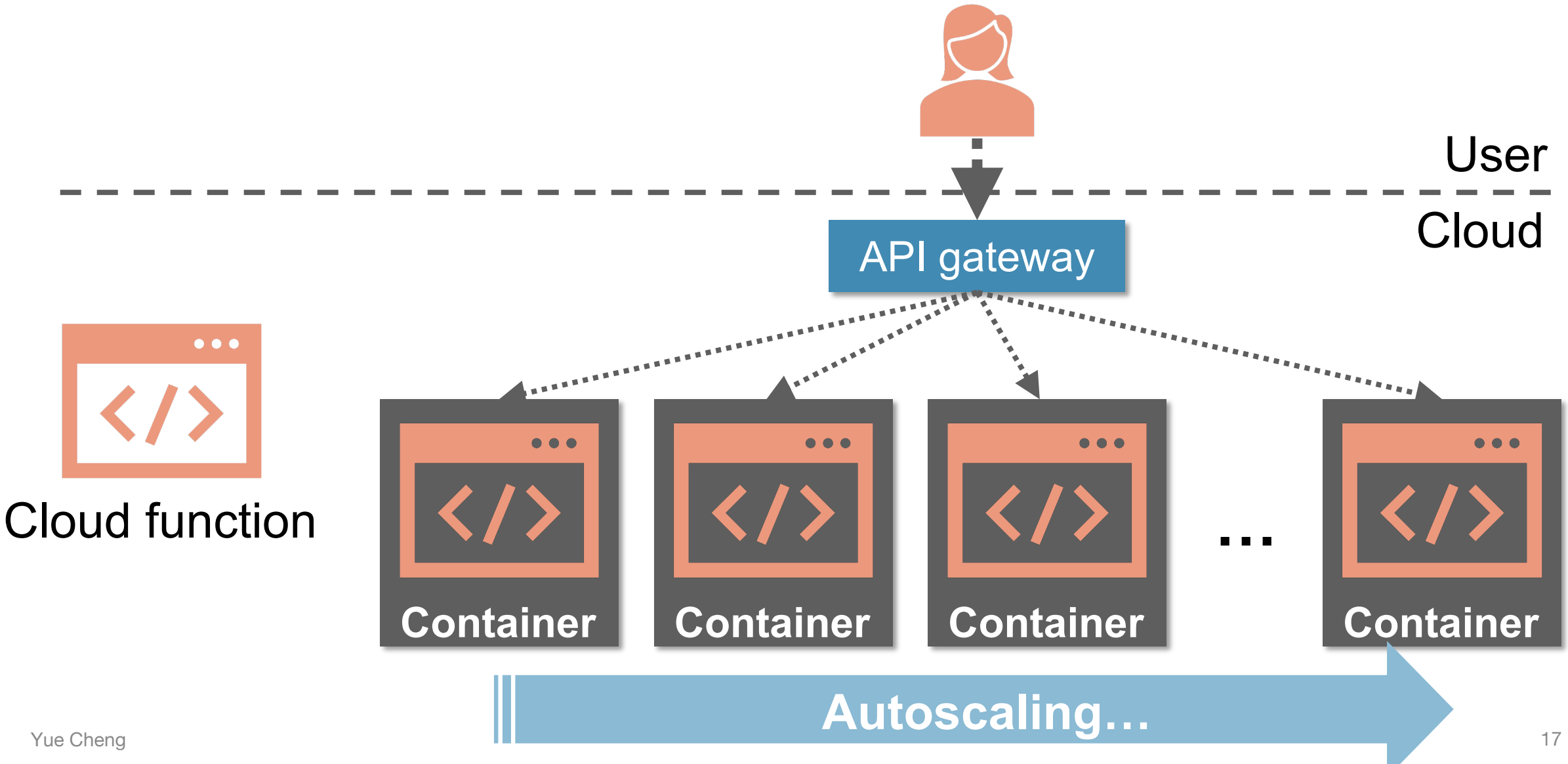
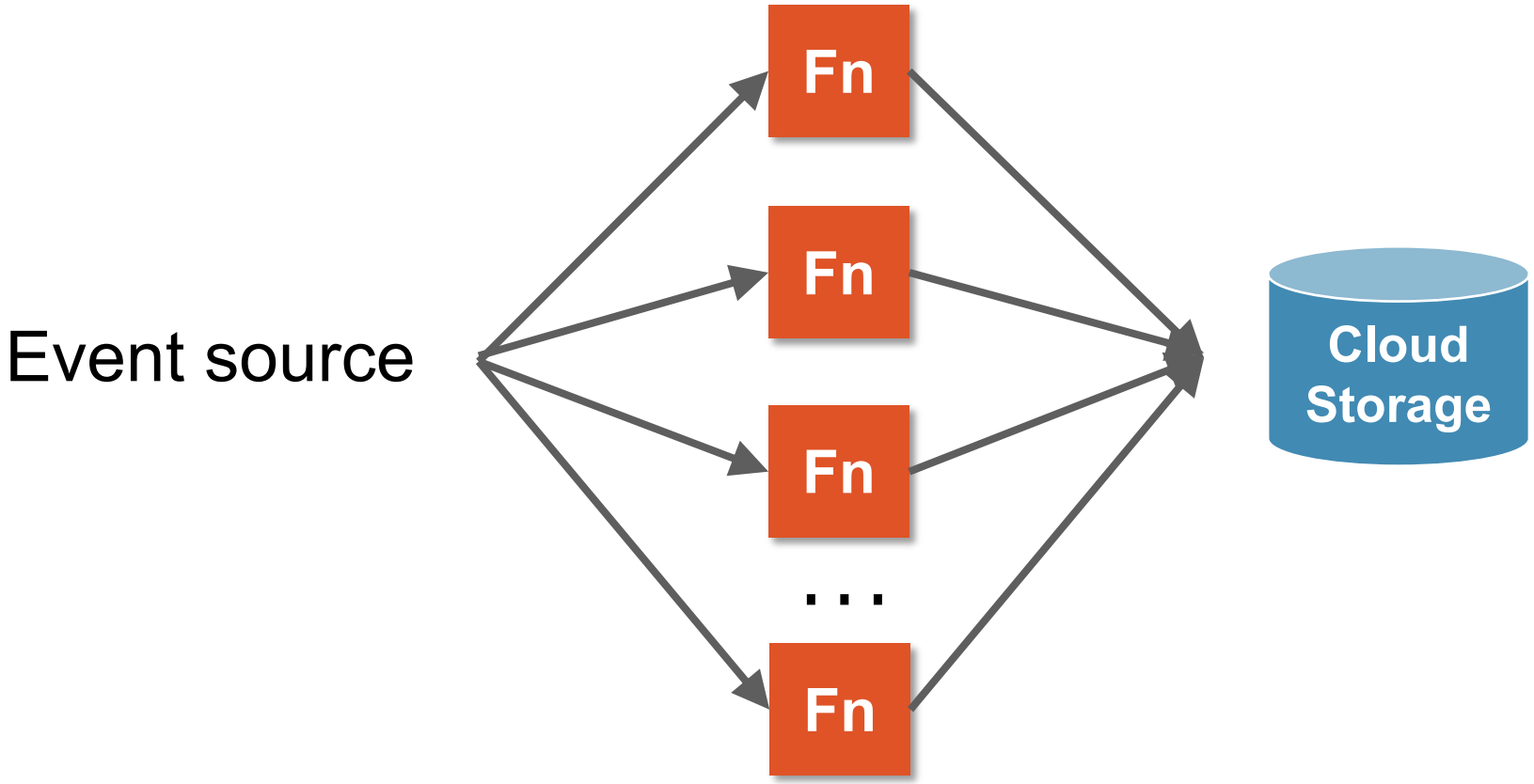


What is FaaS good at today?



Embarrassingly parallel tasks
Stateless processing
...

Limitations of FaaS today

- No guaranteed data availability
- Banned inbound network
- Limited per-function resources
- Limited function execution time

Limitations of FaaS today

- No guaranteed data availability

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⚠ Cloud functions could be reclaimed any time

⚠ In-memory state is lost

Limitations of FaaS today

- No guaranteed data availability
- Banned inbound network
- Limited per-function resources
- Limited function execution time

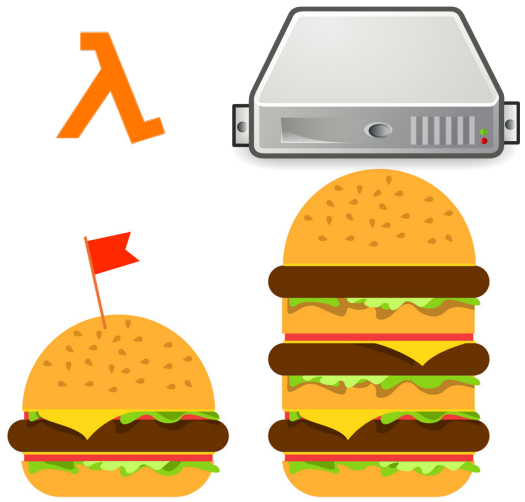
⚠ Cloud functions cannot run as a server

Limitations of FaaS today

- No guaranteed data availability
- Banned inbound network
- Limited per-function resources
- Limited function execution time

⚠ Limited CPU & memory

⚠ I/O is a bottleneck



Limitations of FaaS today

- No guaranteed data availability
- Banned inbound network
- Limited per-function resources
- Limited function execution time

⚠ Limited to up to 15 min

Challenges of supporting stateful apps on FaaS

Research Question: Is FaaS poorly suited for stateful applications because these applications share state?

Case studies:

1. **[Programming model]** How to design FaaS-centric parallel computing to **enable easy programming of 10,000 CPU cores and 15,000 GBs of RAM**?
2. **[Data storage]** How to exploit FaaS **elasticity and pay-per-use** to reduce the $$ cost by **100X**?

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Python analytics: What we have today

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def MyFunc(X, Y):
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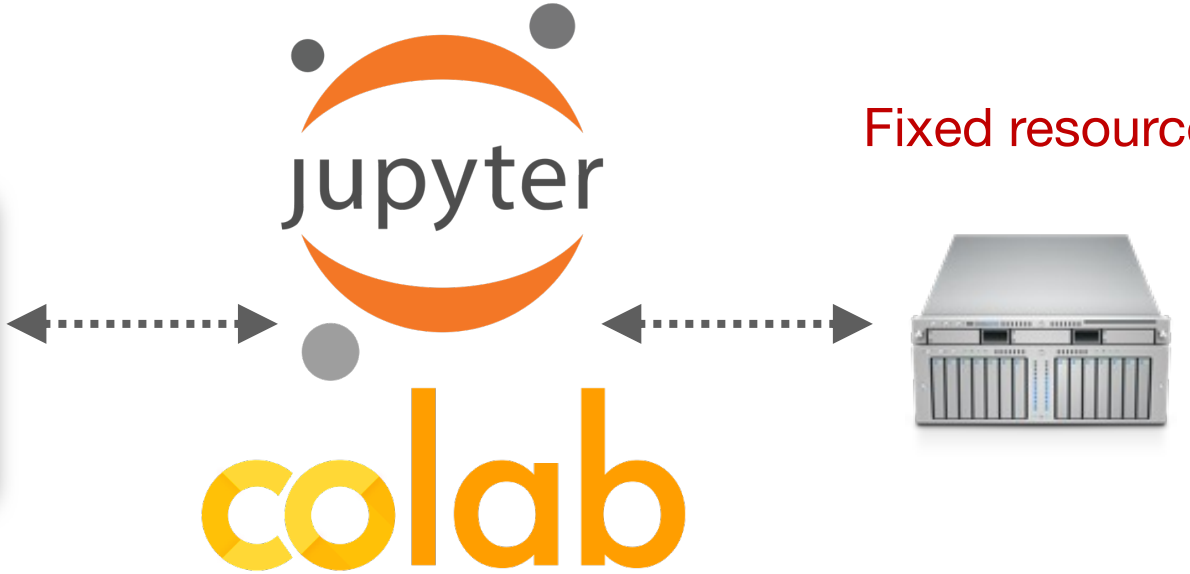

Fixed resource

User writes interactive analytics and runs it on a notebook server

- No autoscaling for large computations
- Too slow? OOM? Need to scale out manually!
- Too expensive? Idled resources charge $$

Python analytics: What we have today

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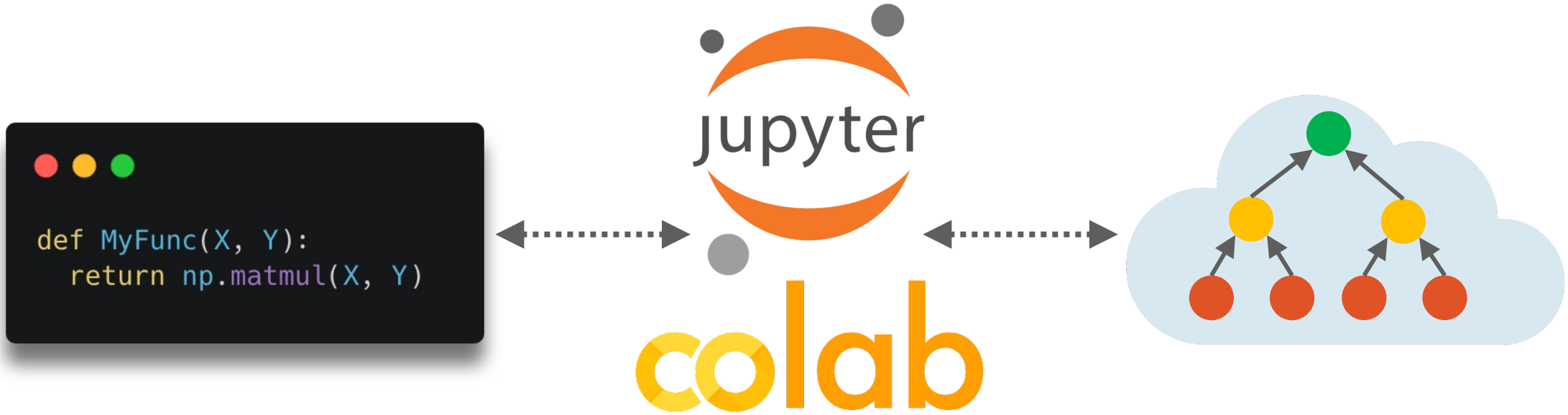
Manually deployed
distributed computing cluster

User writes interactive analytics and runs it on a notebook server

- No autoscaling for large computations
- Too slow? OOM? Need to scale out manually!
- Too expensive? Idled resources charge $$

High barriers to enter for those who lack CS/systems background

Python analytics: What we would like to have



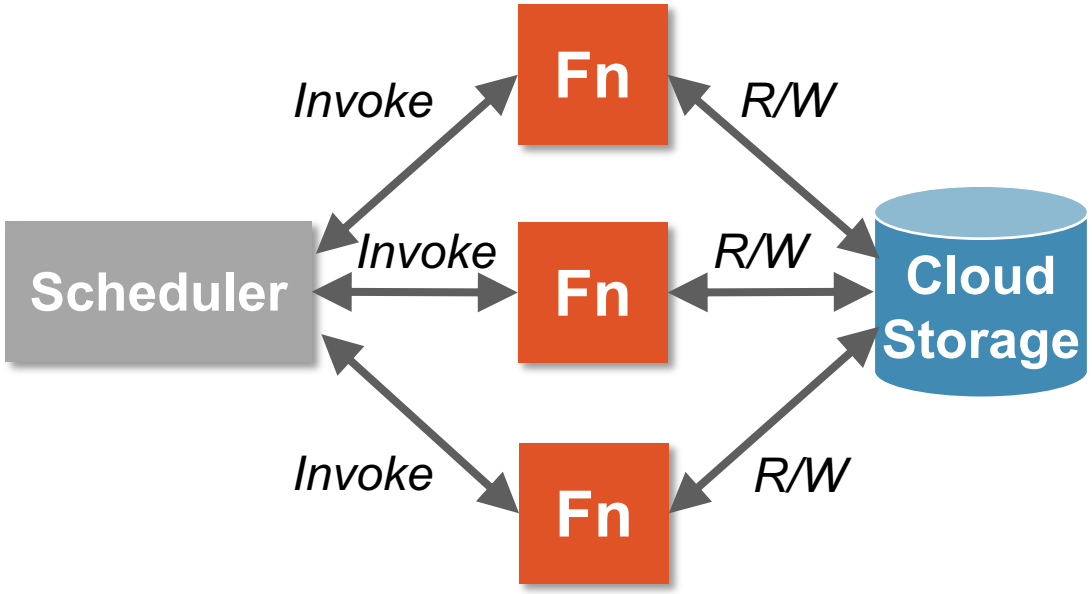
User writes interactive analytics and runs it **on FaaS**

- Elastically & automatically scales to right size
- Pay-per-use with minimal $$ cost
- Expertise of writing parallel programs **NOT required**
- Manual cluster maintenance **NOT required**

Quantifying the pain of FaaS

Or, how FaaS adds huge amounts of **performance taxes**

Python analytics on FaaS is too slow!



State-of-the-art FaaS frameworks

* [PyWren] Occupy the Cloud: Distributed Computing for the 99%. In ACM SoCC'17.
* [numpywren] Serverless linear algebra. In ACM SoCC'20.

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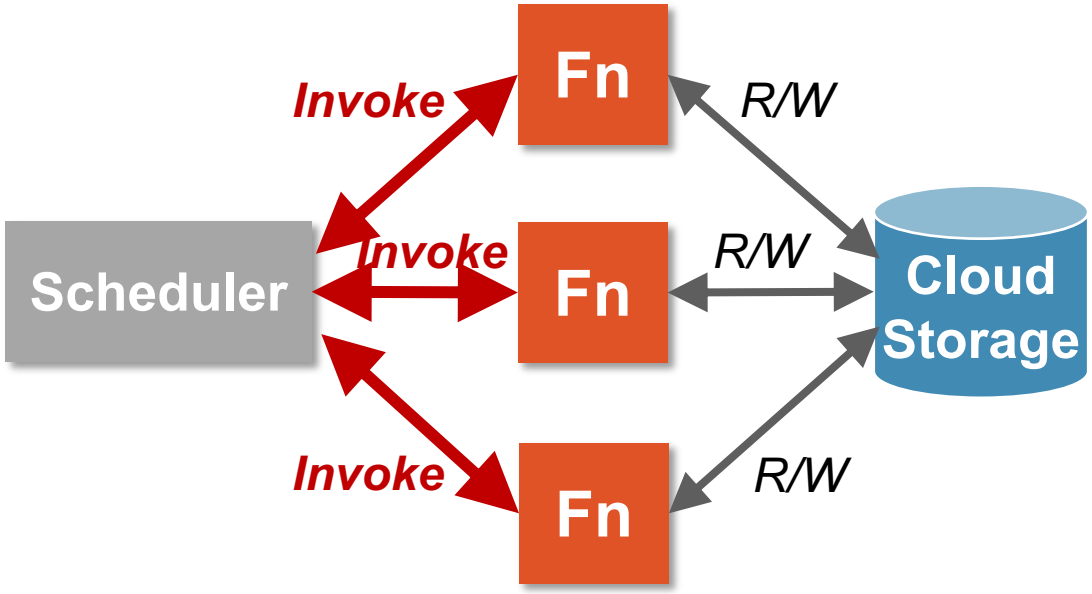

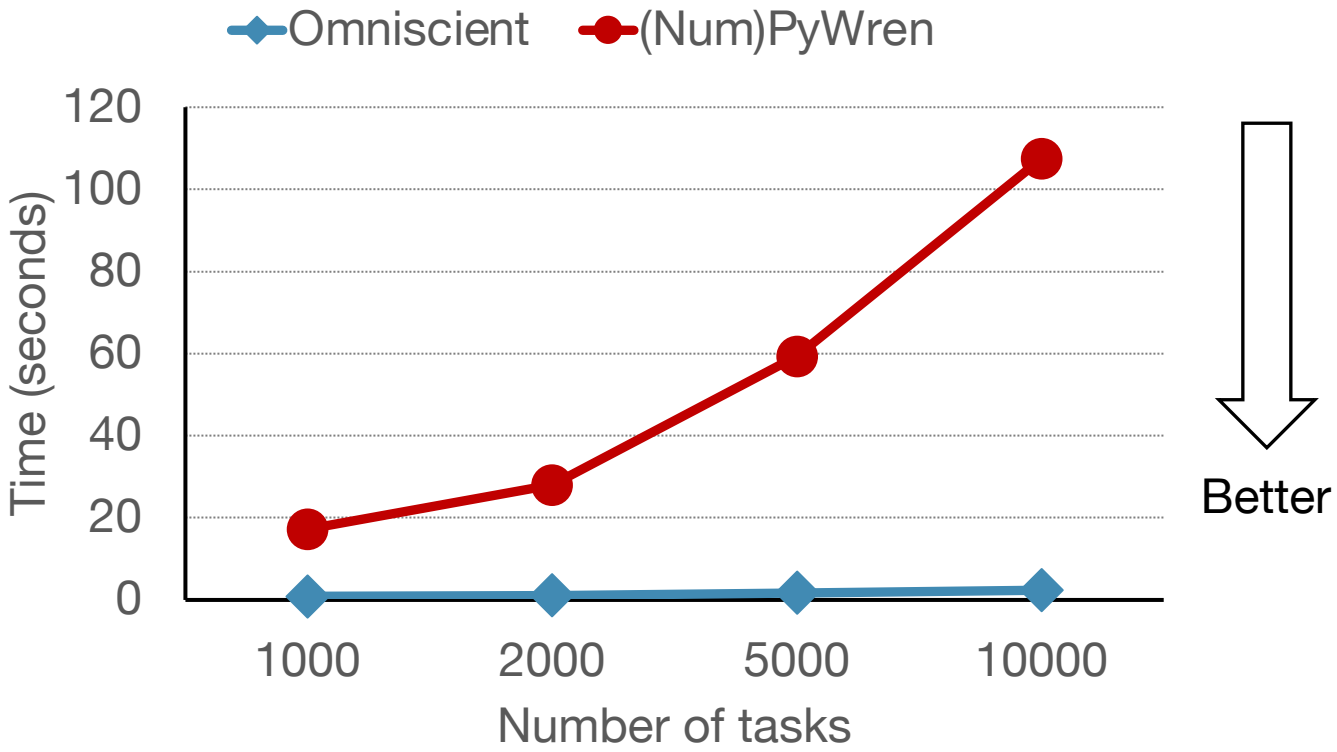

State-of-the-art FaaS frameworks pay huge amounts of FaaS taxes

- **Task scheduling bottleneck:** Too slow to scale to thousands of functions

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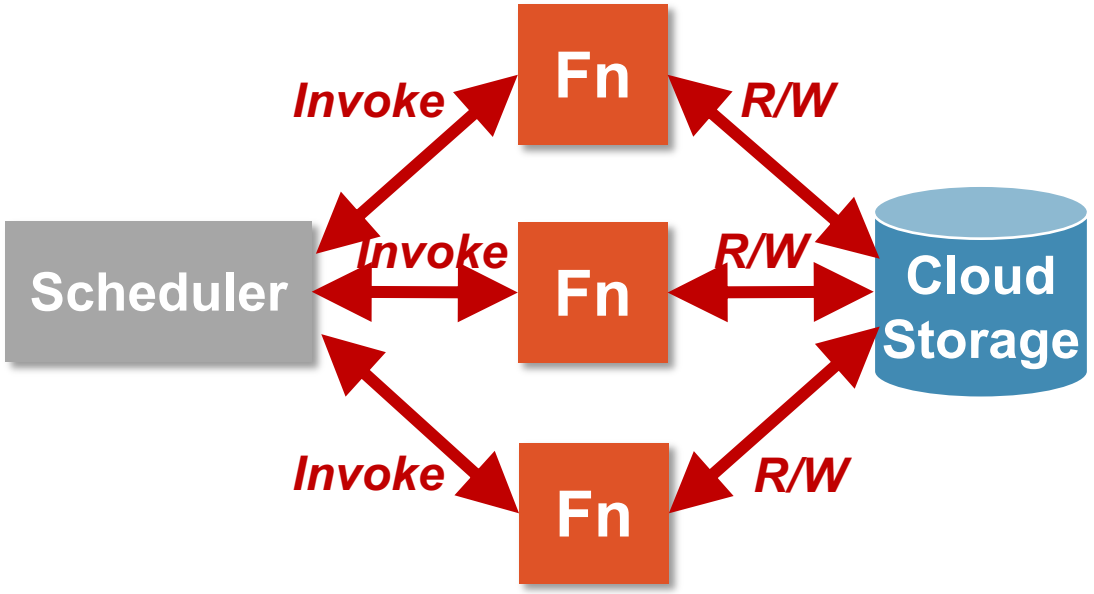

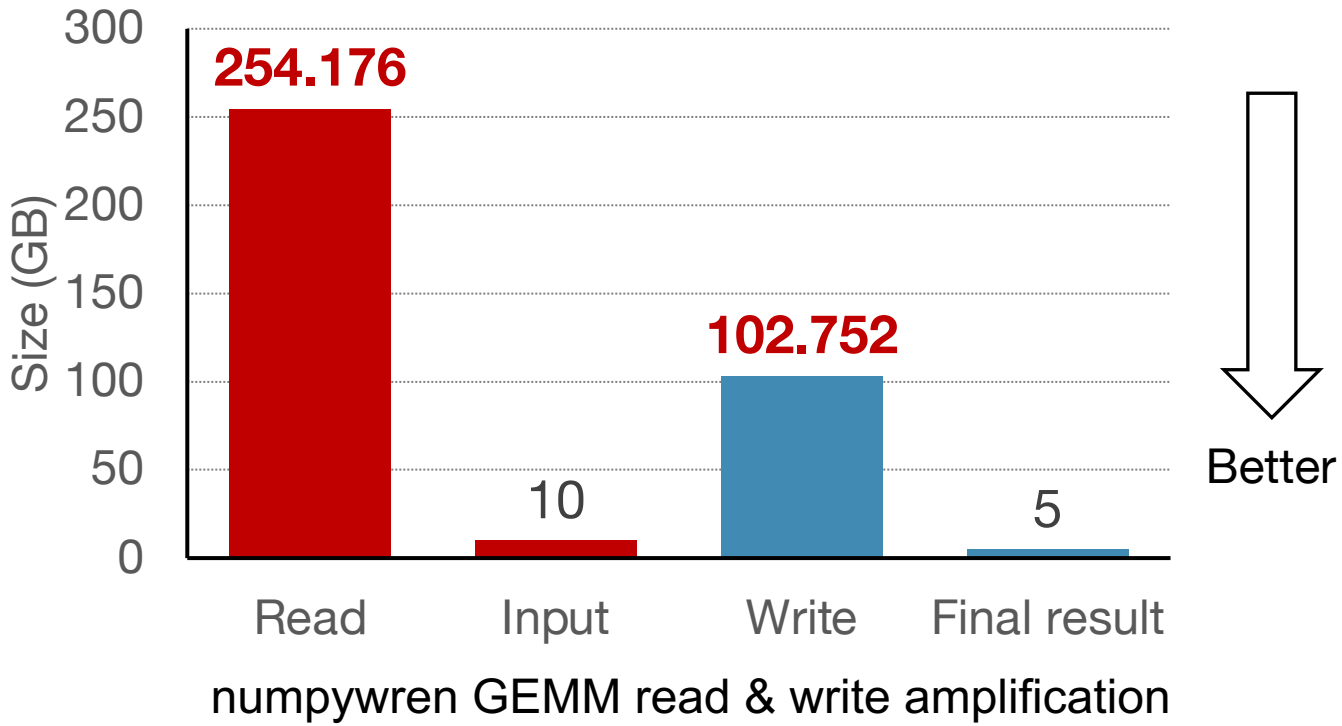

numpywren GEMM read & write amplification

State-of-the-art FaaS frameworks pay huge amounts of FaaS taxes

- **Task scheduling bottleneck:** Too slow to scale to thousands of functions
- **I/O bottleneck:** Excessive data movement cost due to FaaS constraint

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Python analytics on FaaS is too slow!

Naively porting a stateful application to a FaaS platform won't work!

Think like a function: A FaaS-centric approach

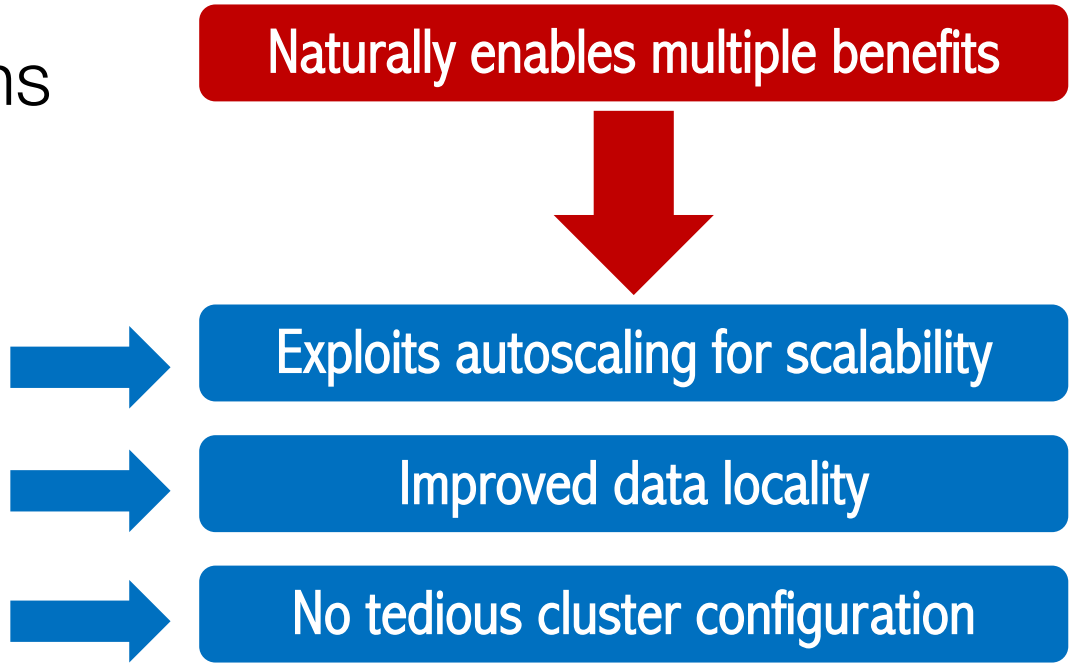
Insight: A FaaS framework may not care about traditional metrics (load balancing, cluster util.)

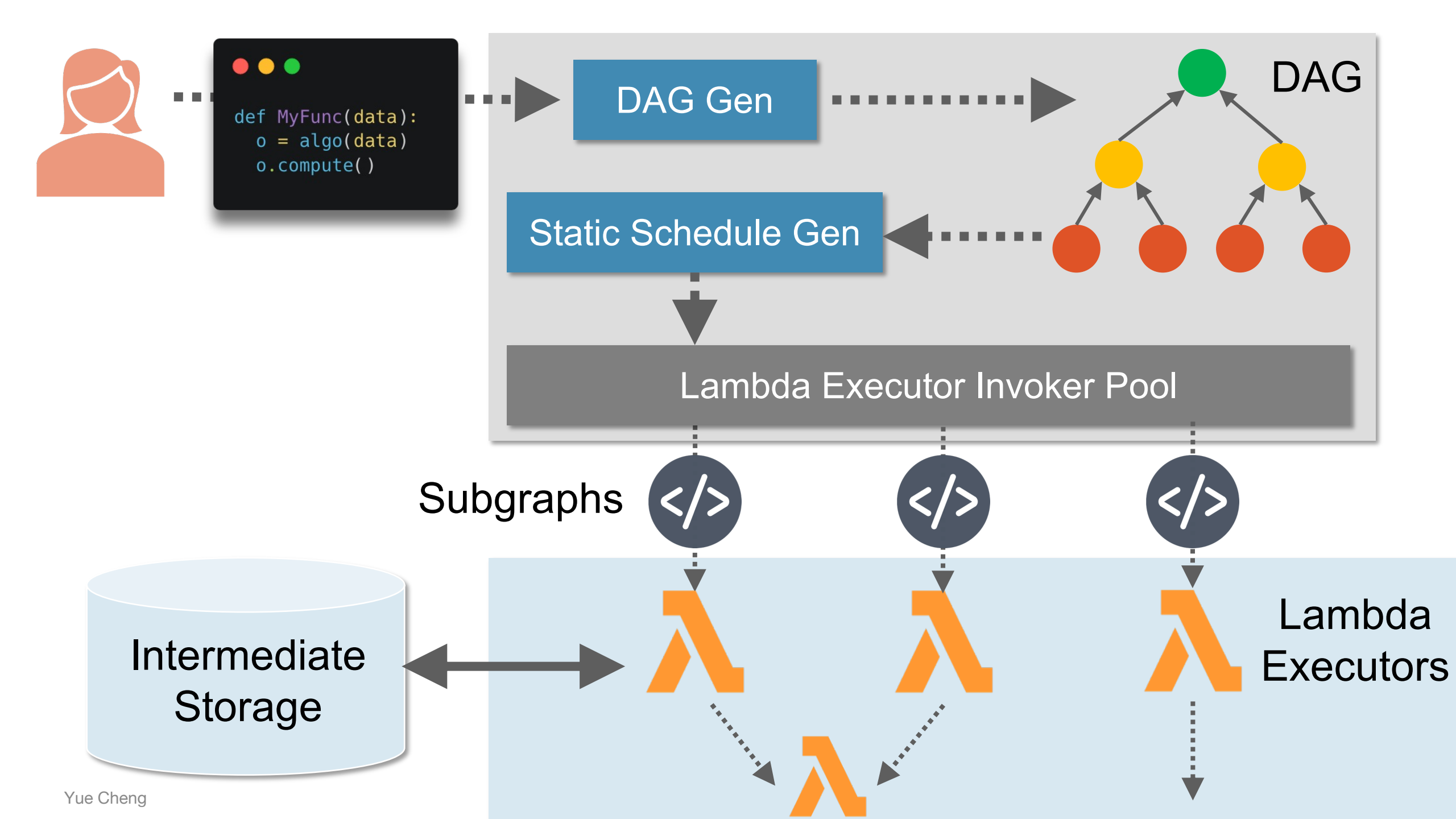
Enter Wukong

Wukong is a **FaaS-centric** parallel computing framework

Key idea: Partitions the work of a centralized scheduler across many functions to take advantage of FaaS elasticity

- Functions schedule tasks by invoking functions
- Functions execute multiple tasks to reduce data movement cost
- Functions scale out / in autonomously

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o.compute()
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DAG
Static Schedule Gen
Lambda Executor Invoker Pool
Subgraphs
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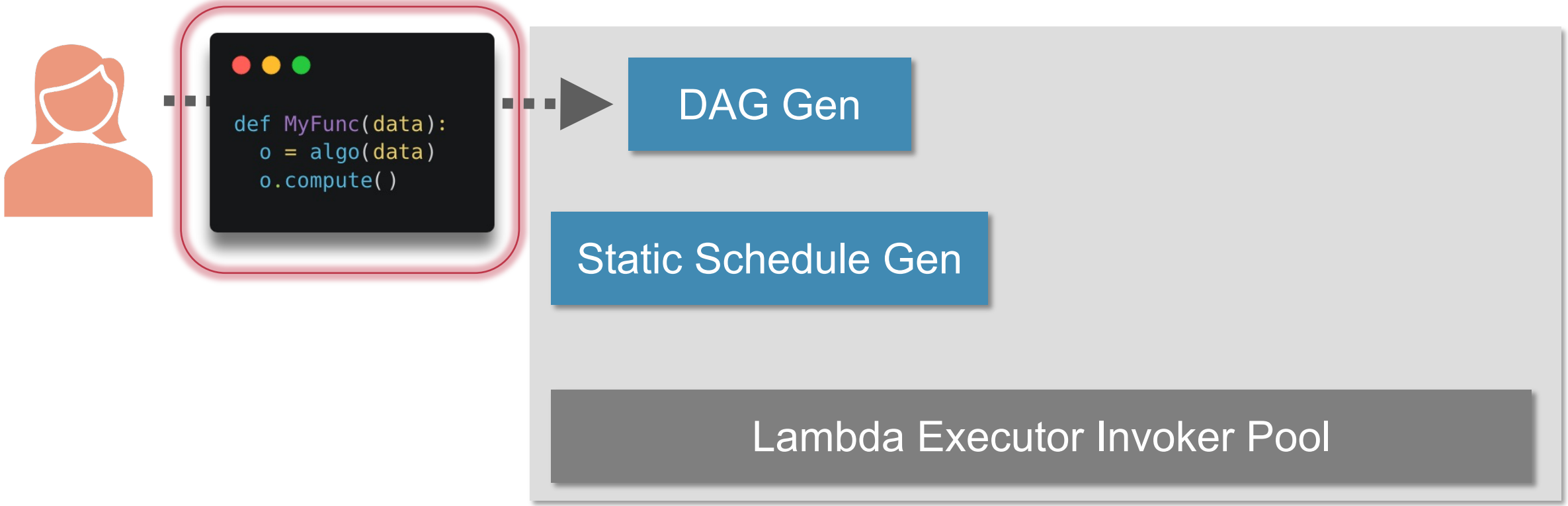
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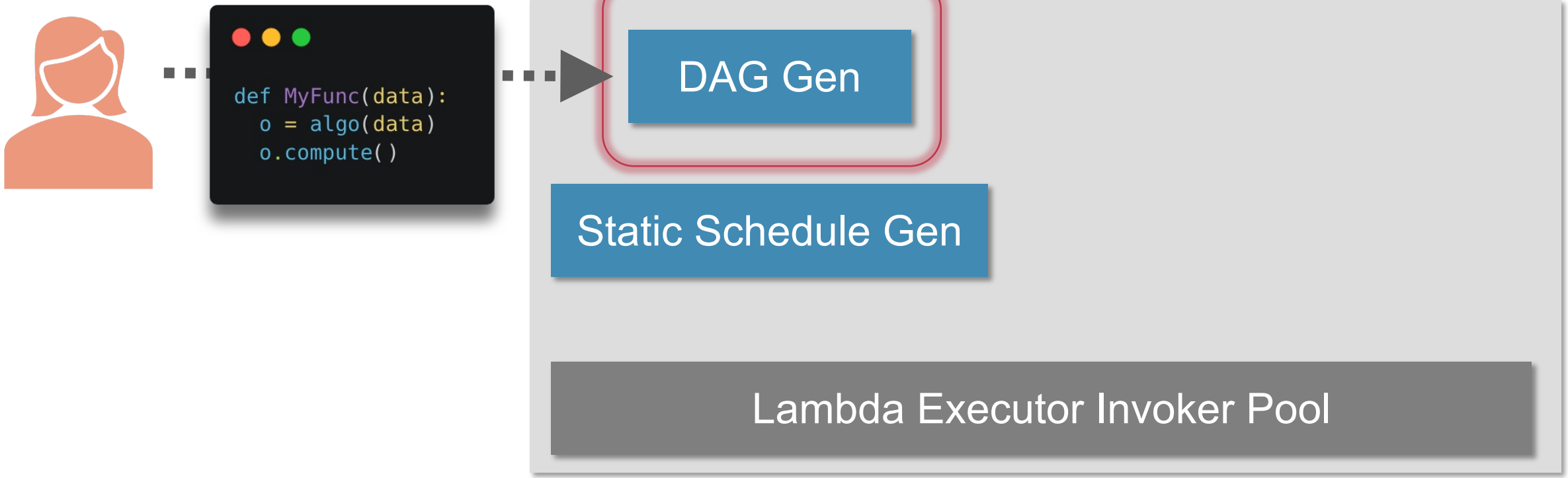
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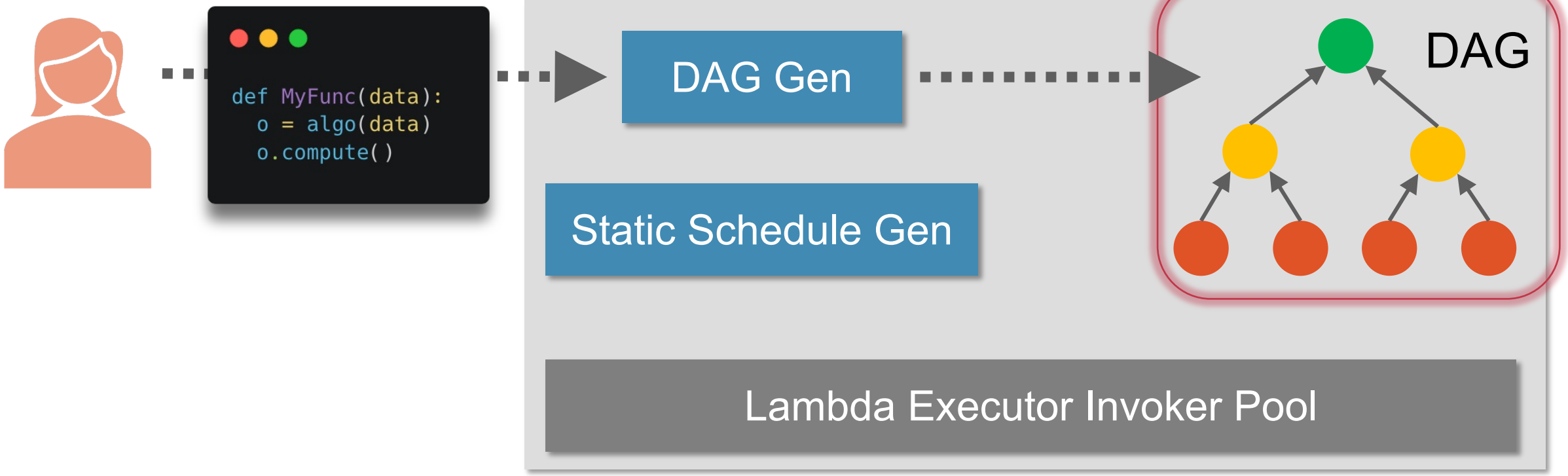
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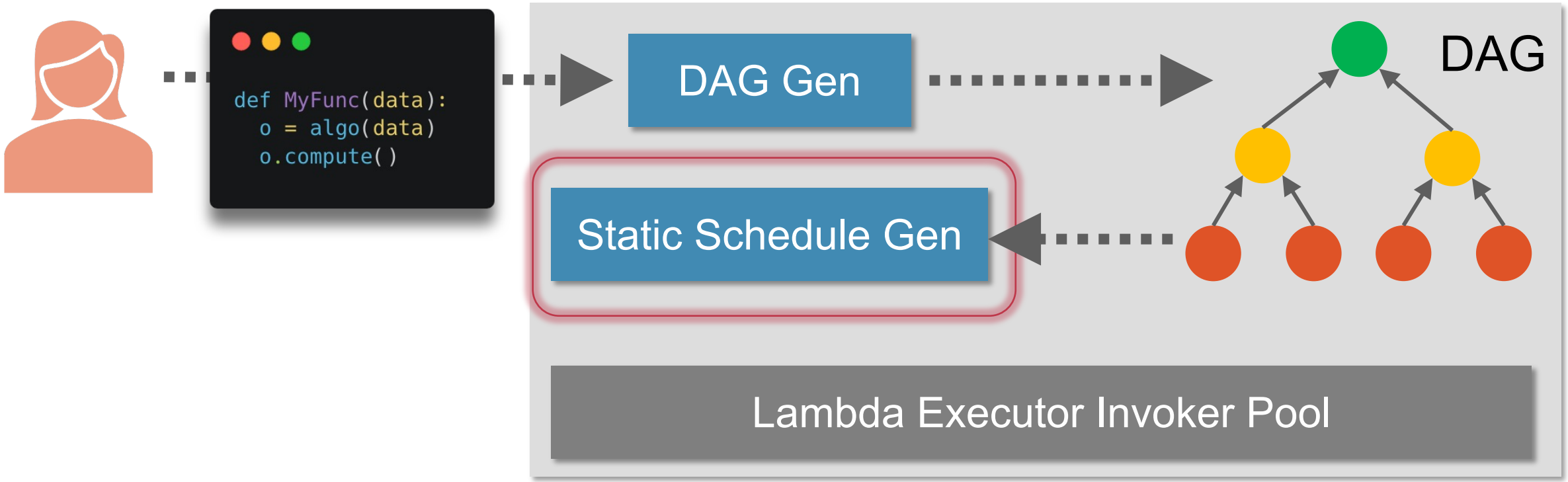
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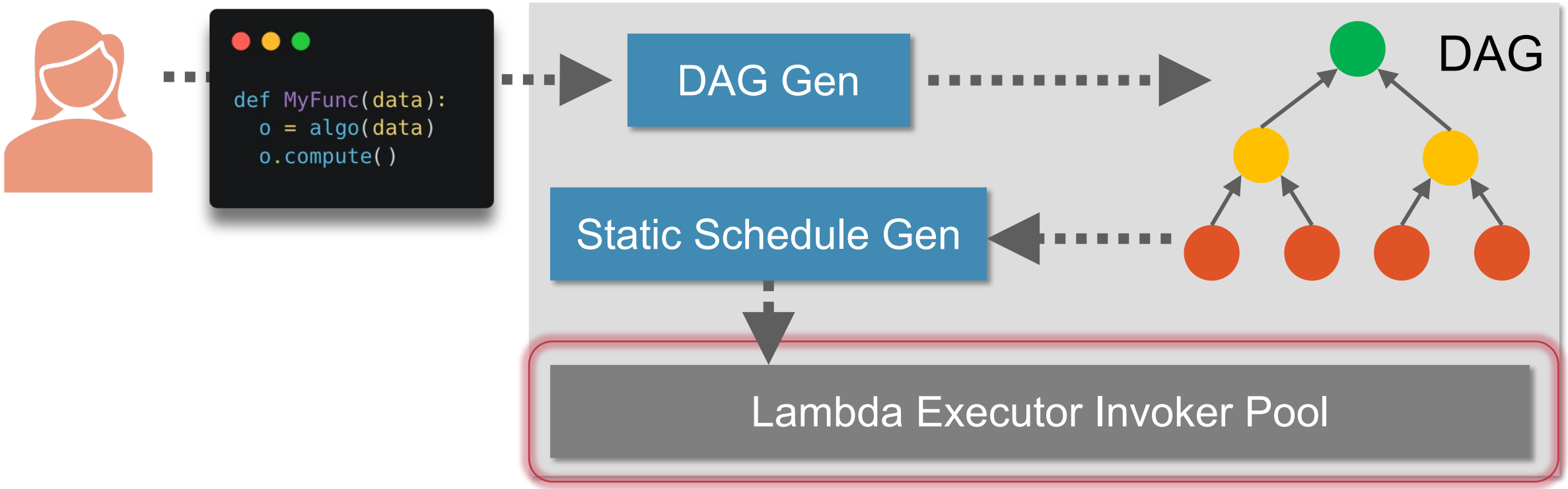
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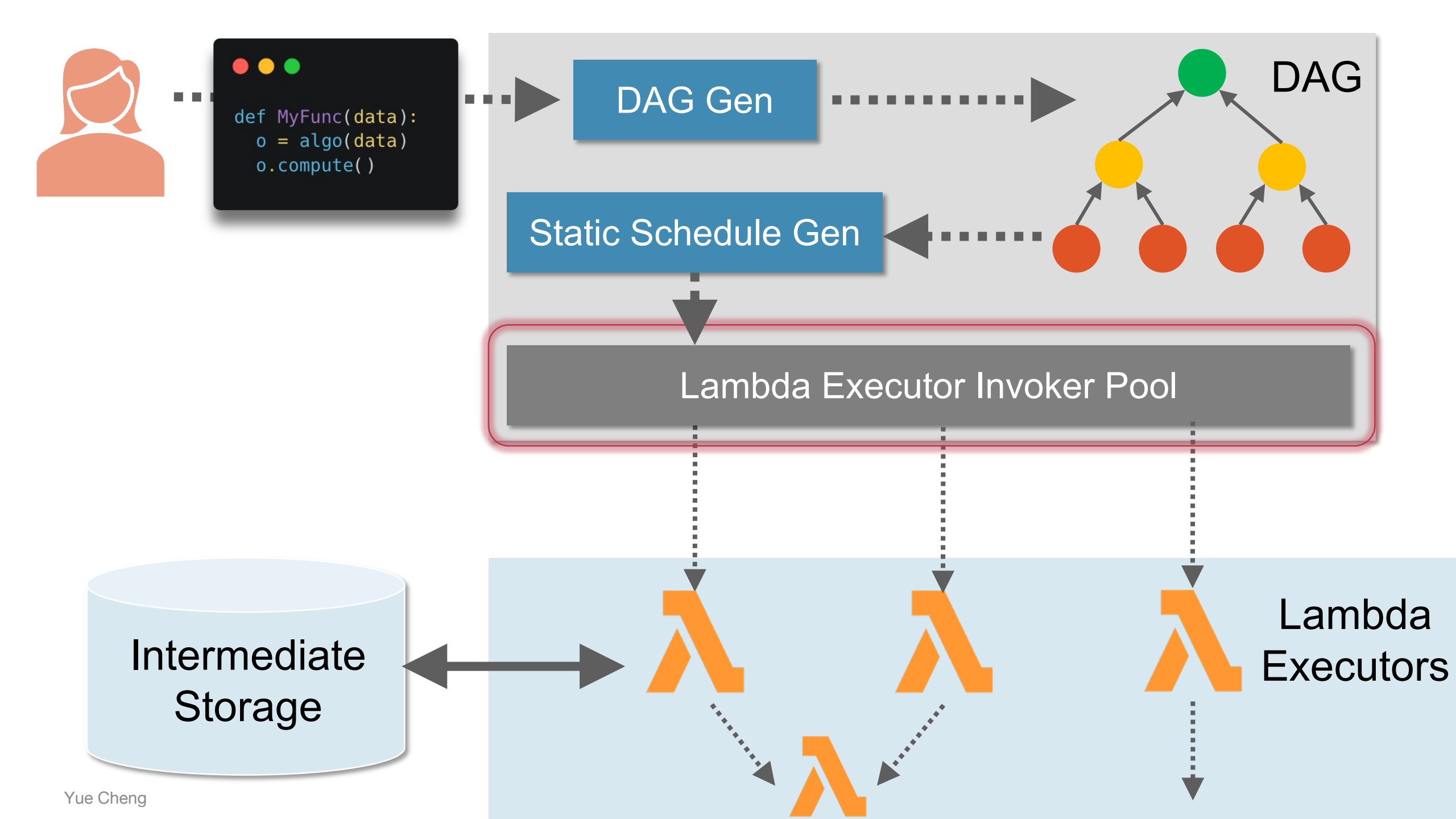
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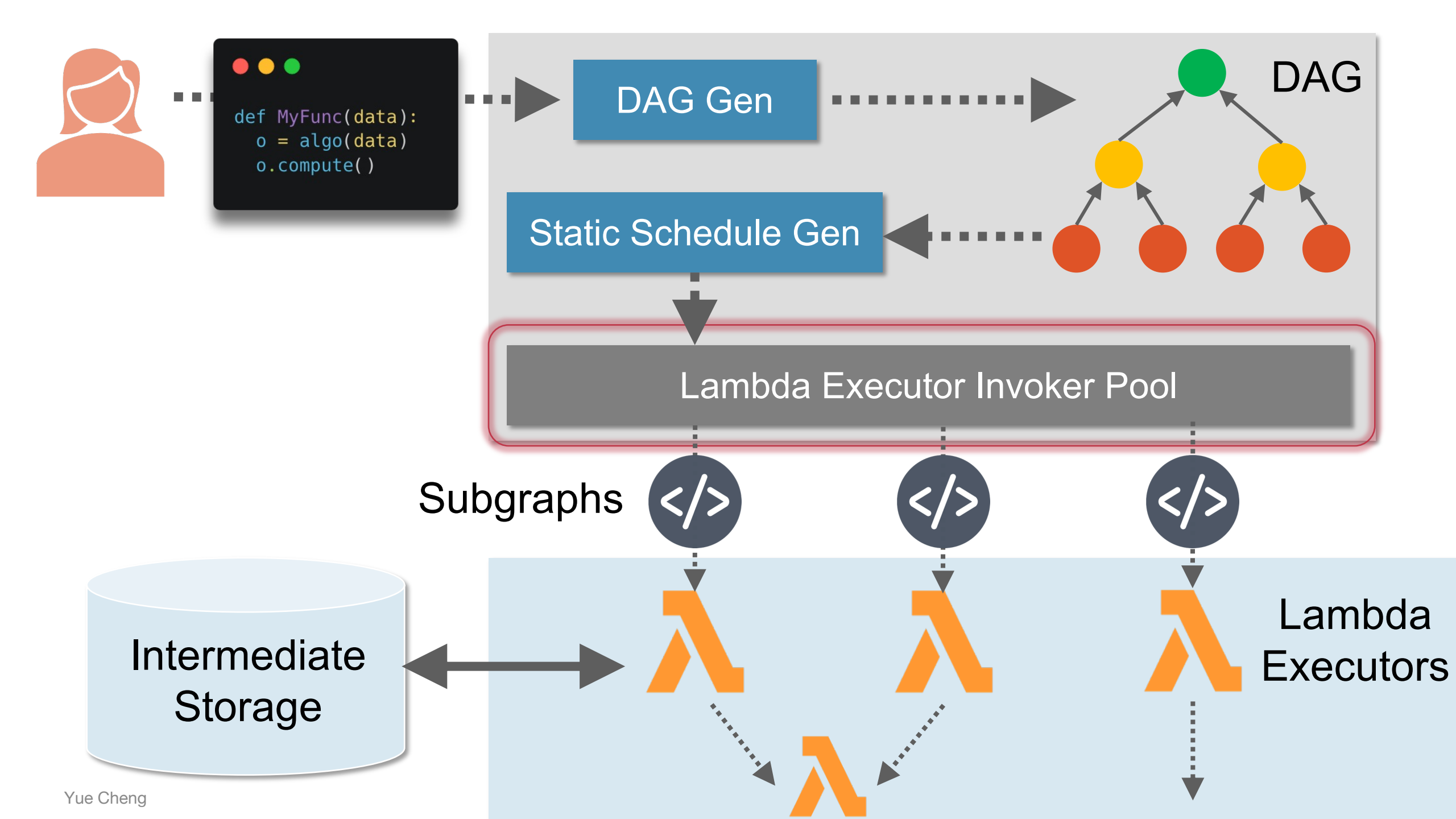
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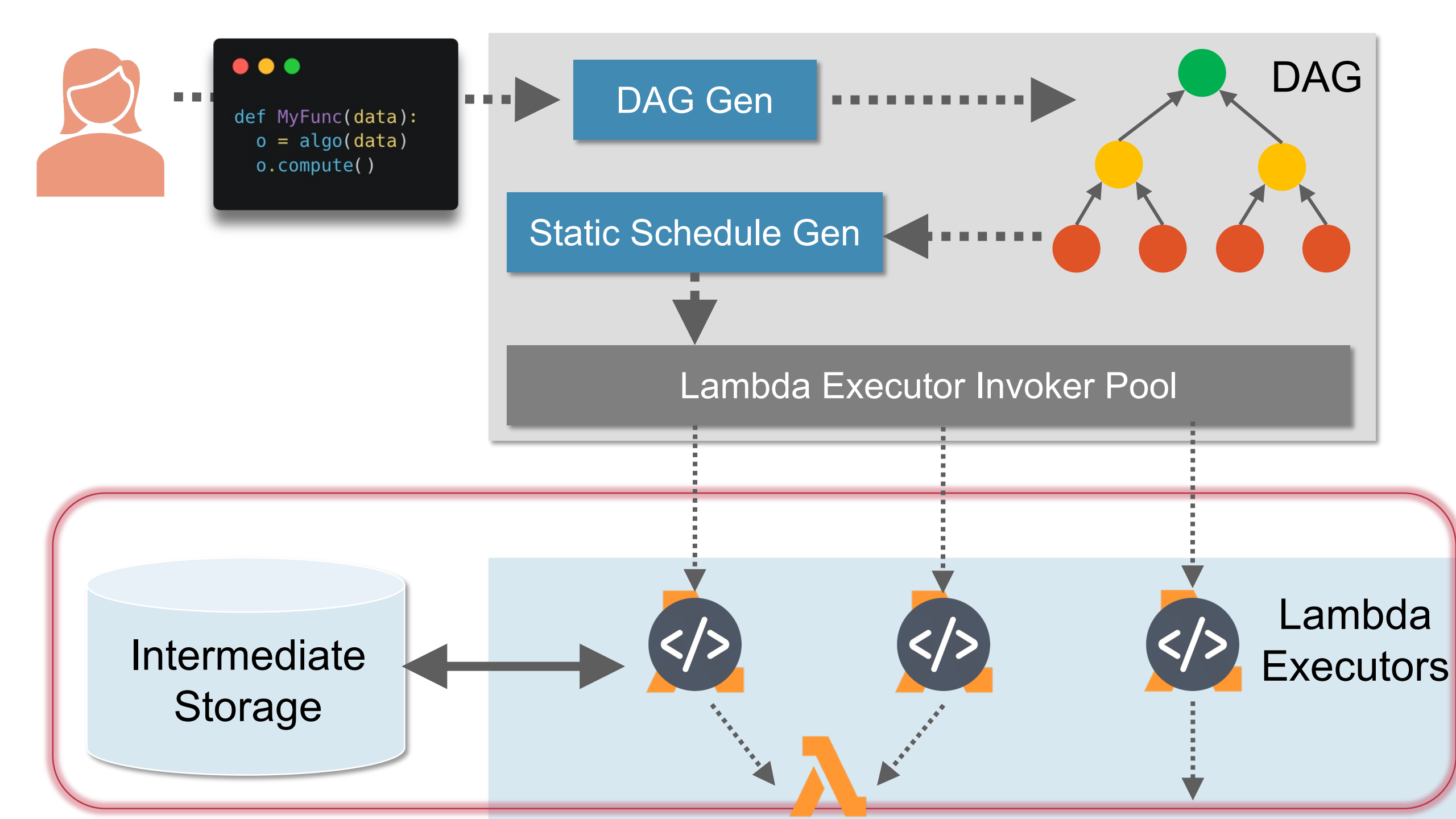
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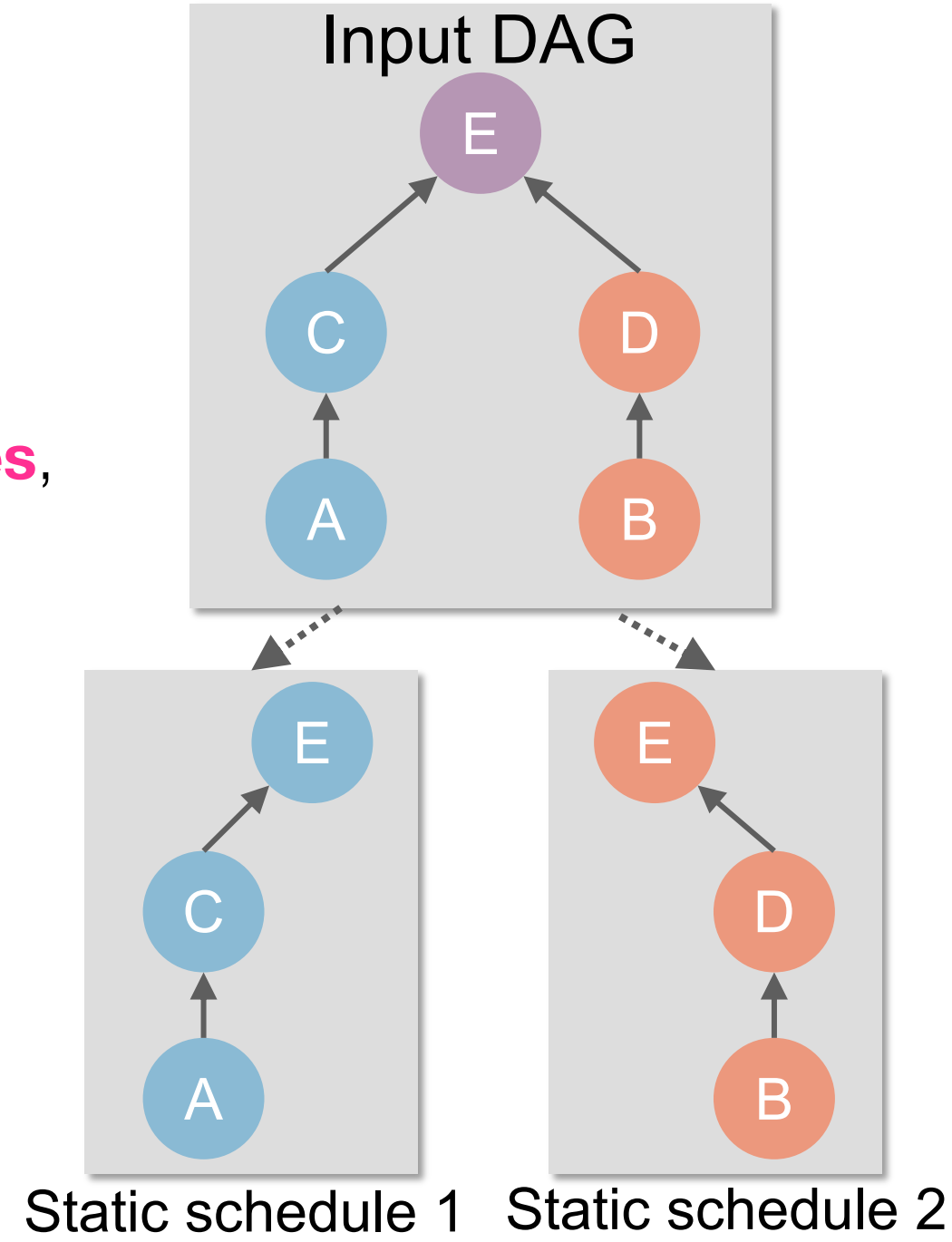
Scheduling in Wukong

- Combination of **static** and **dynamic** scheduling
- Input DAG partitioned into **static schedules**, or subgraphs of the original DAG
- Serverless executors are assigned a **static schedule**
- Executors use **dynamic scheduling** to enforce data dependencies and **cooperatively** schedule tasks found in multiple static schedules



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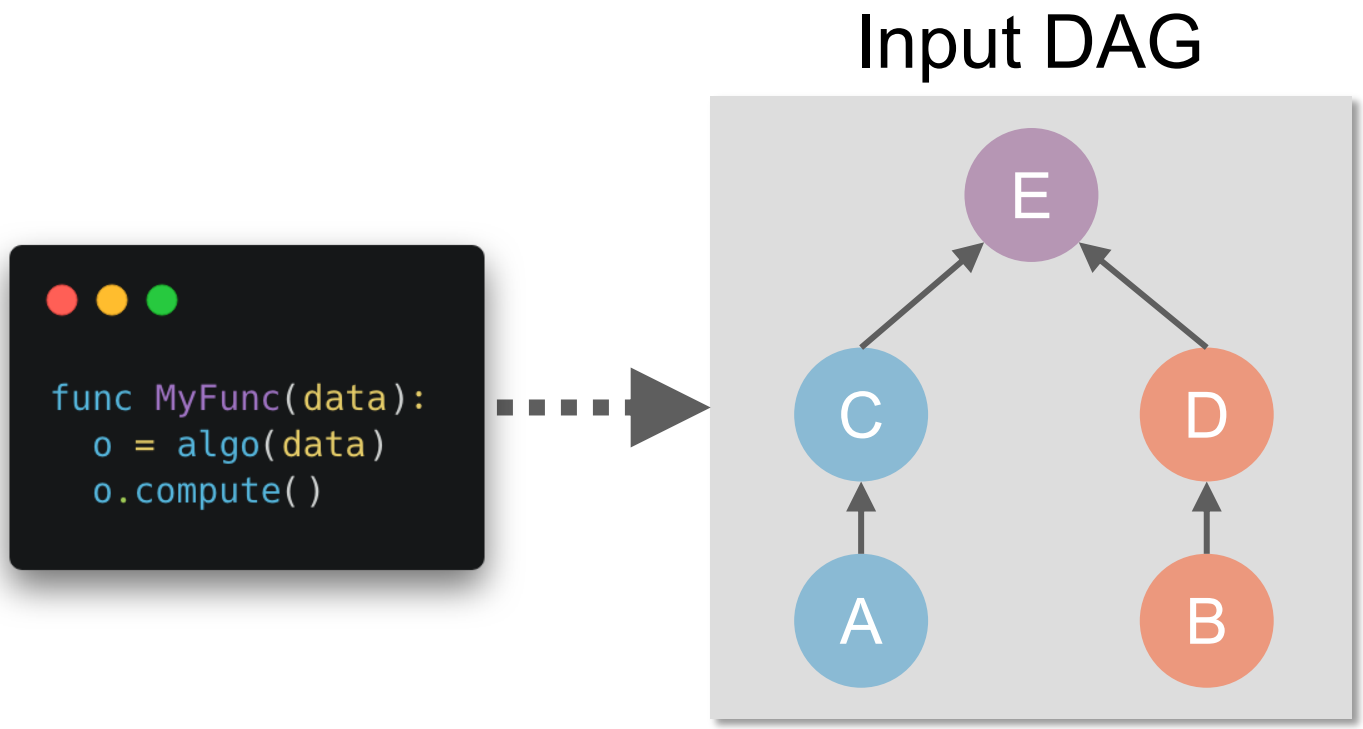
Static scheduling

Static scheduling



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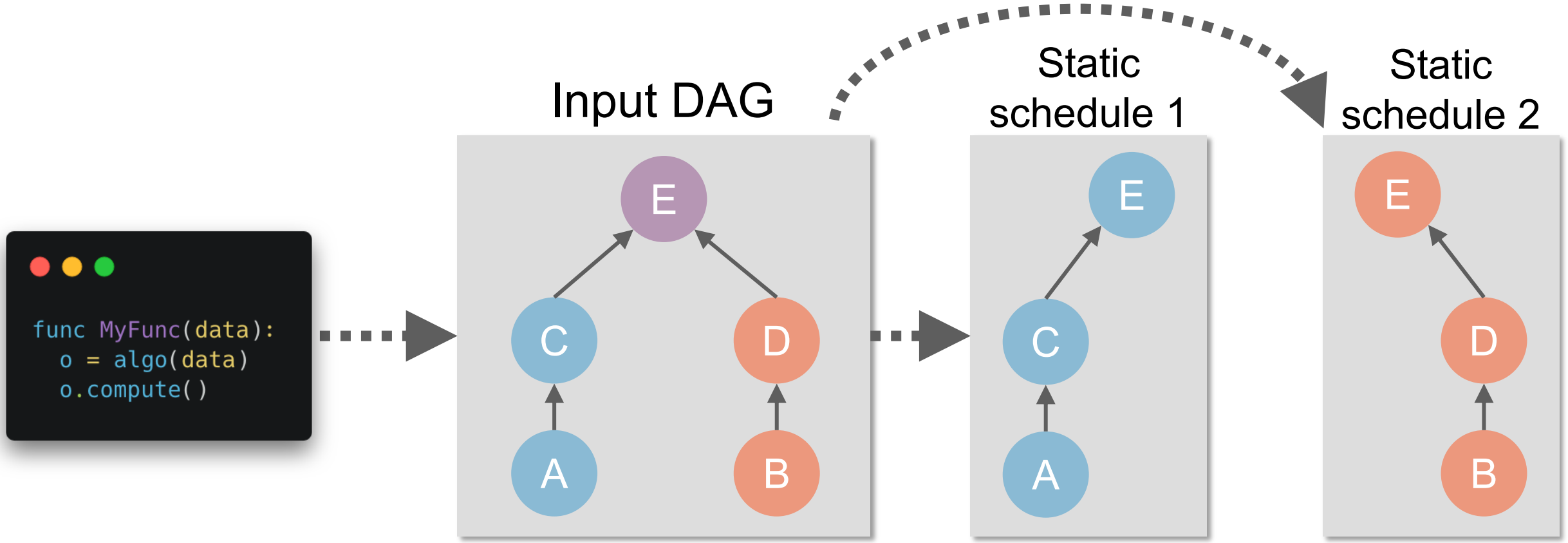

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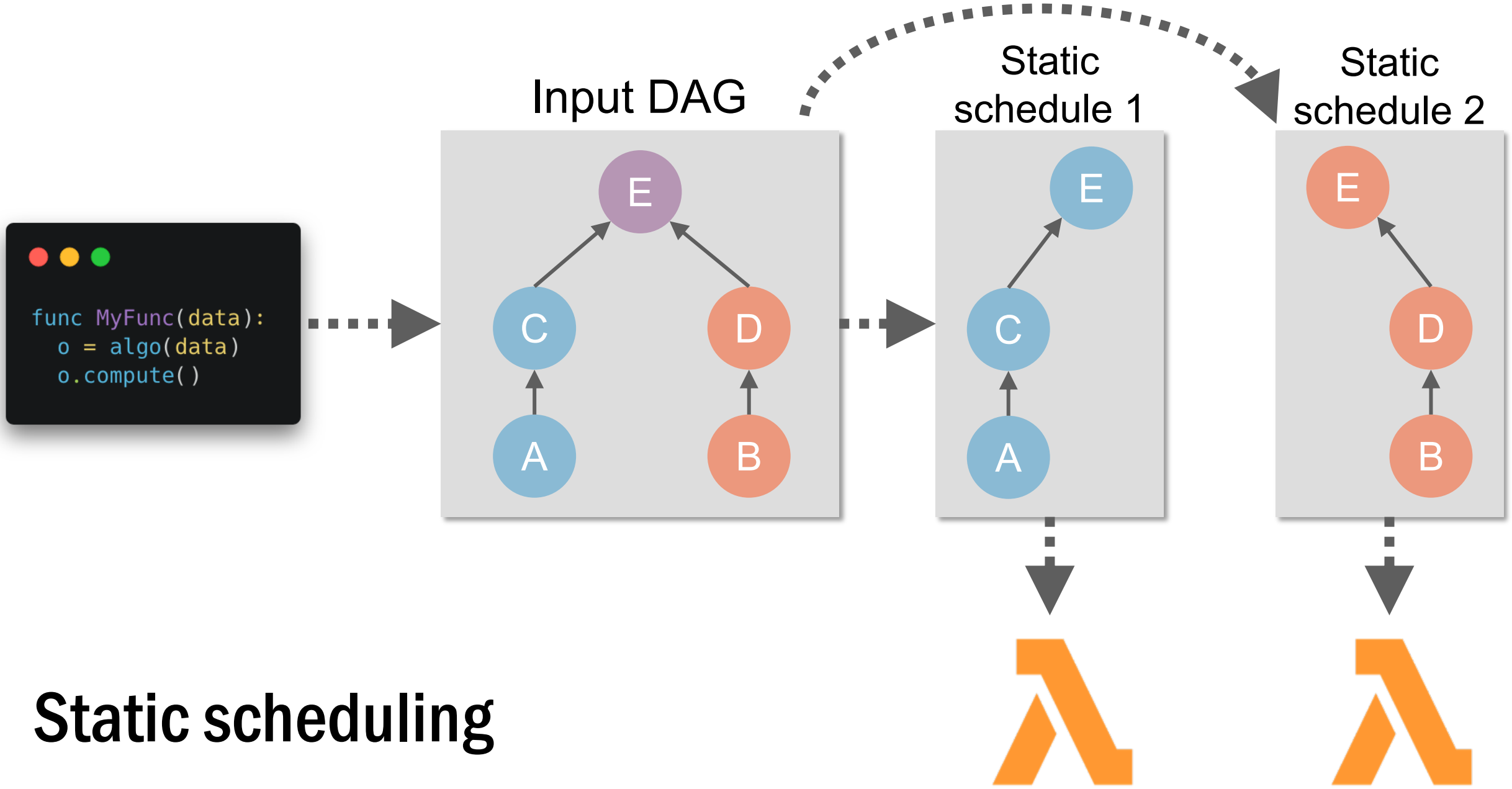

Static scheduling

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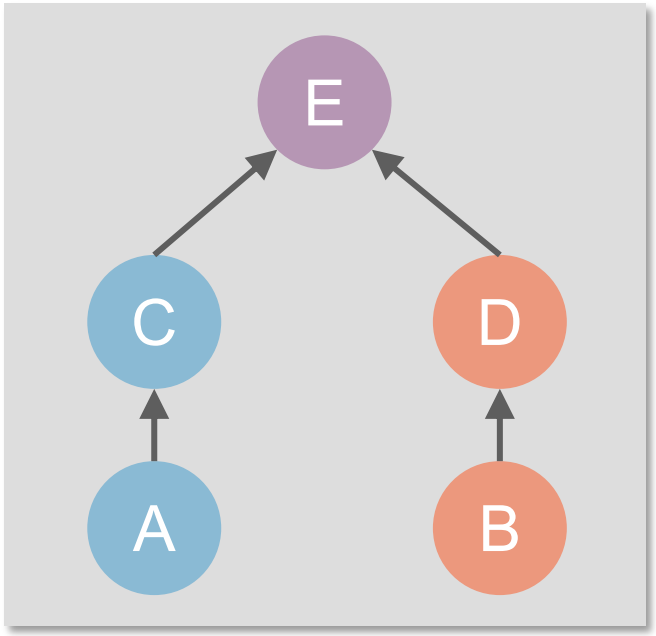
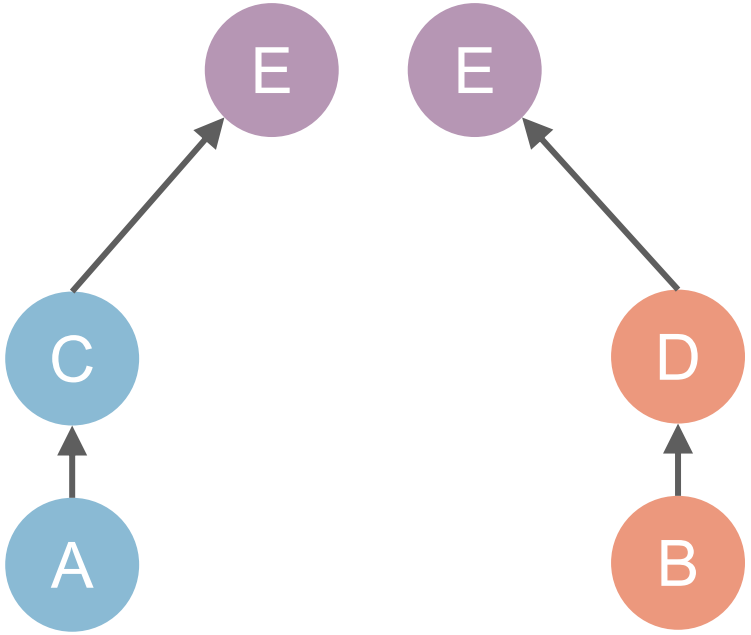


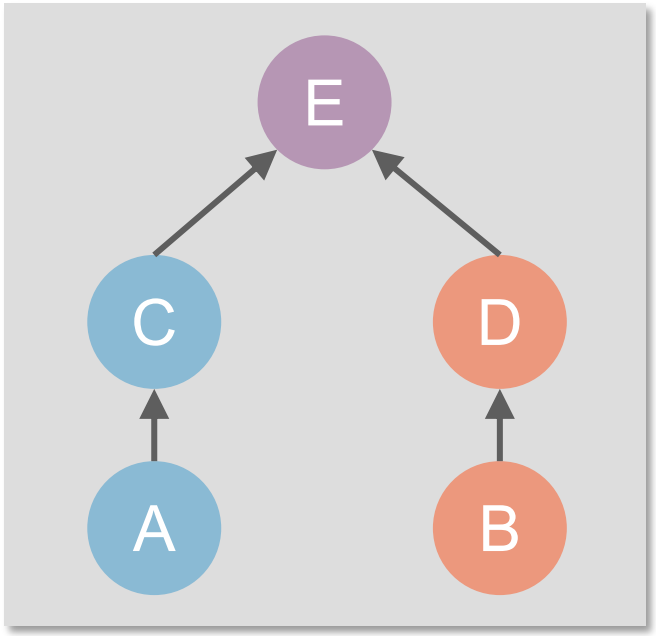


Dynamic scheduling

Executor 1

Executor 2

Input DAG



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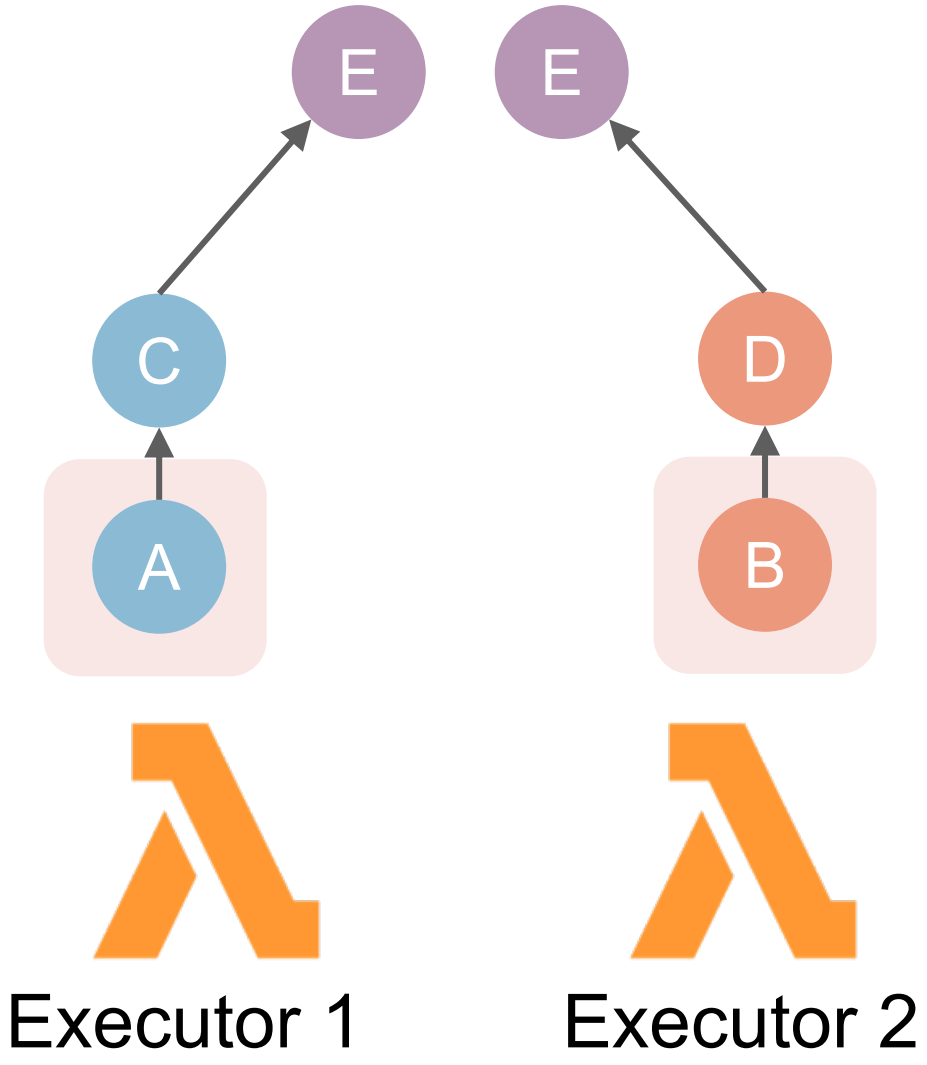

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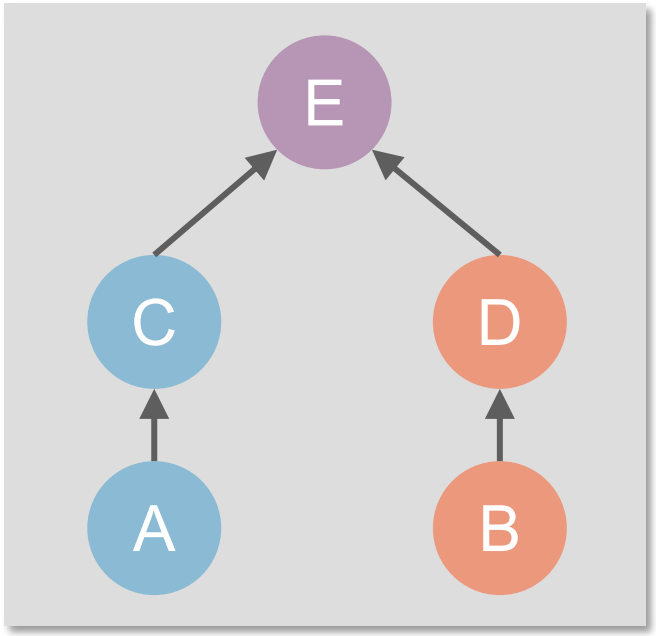
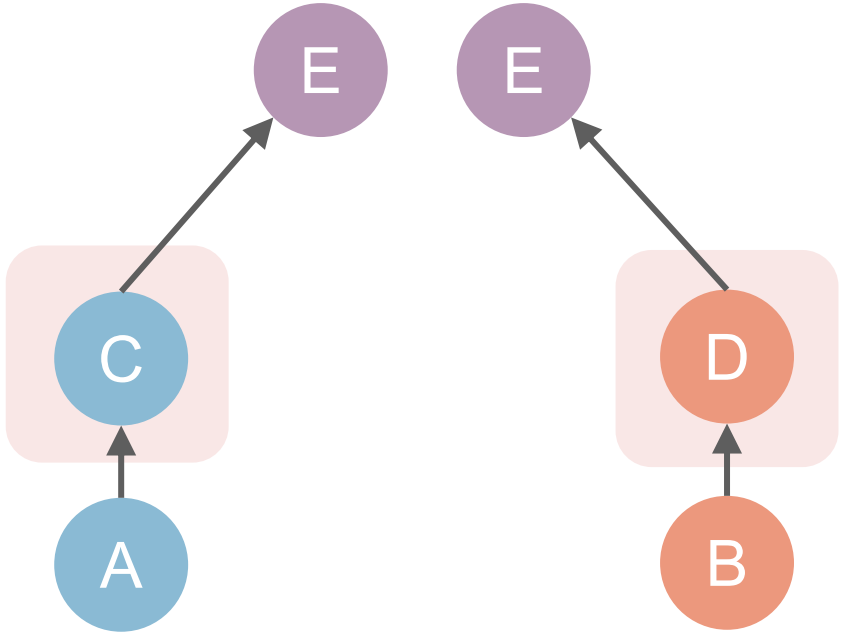


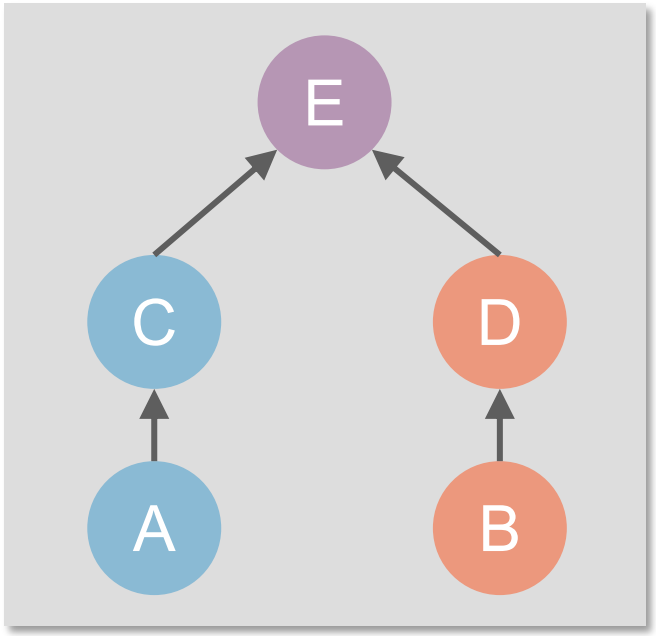


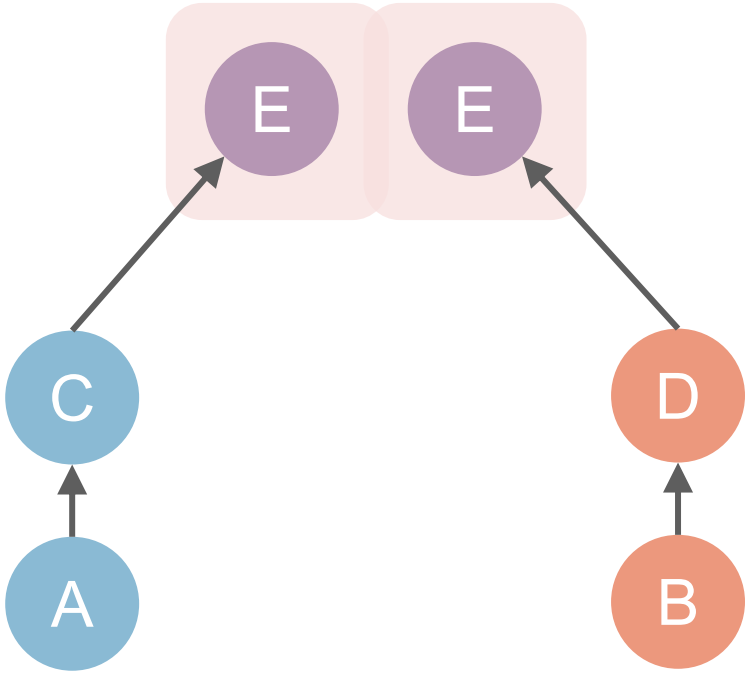
Dynamic scheduling

Executor 1

Executor 2

Input DAG





Dynamic scheduling

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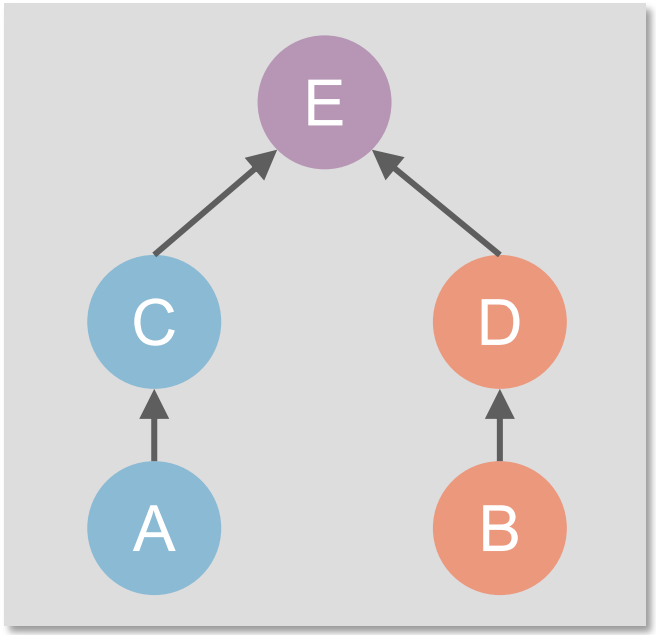
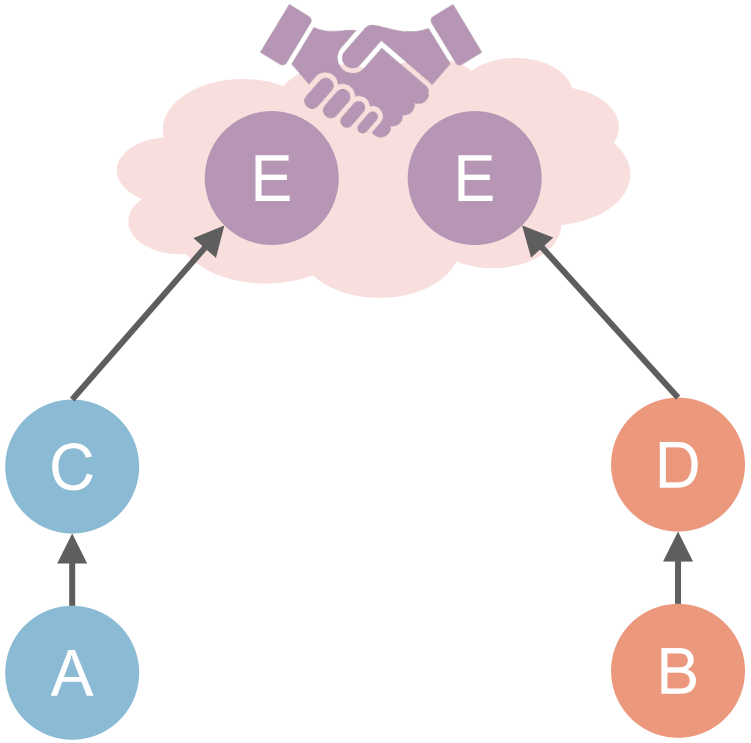


Cooperate



Dynamic scheduling

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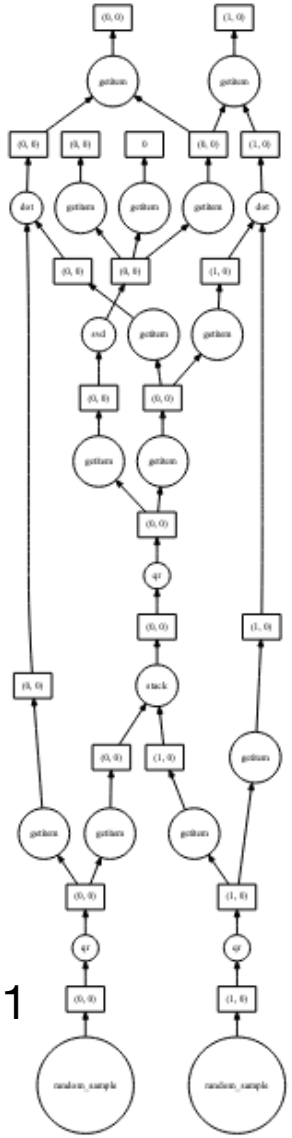
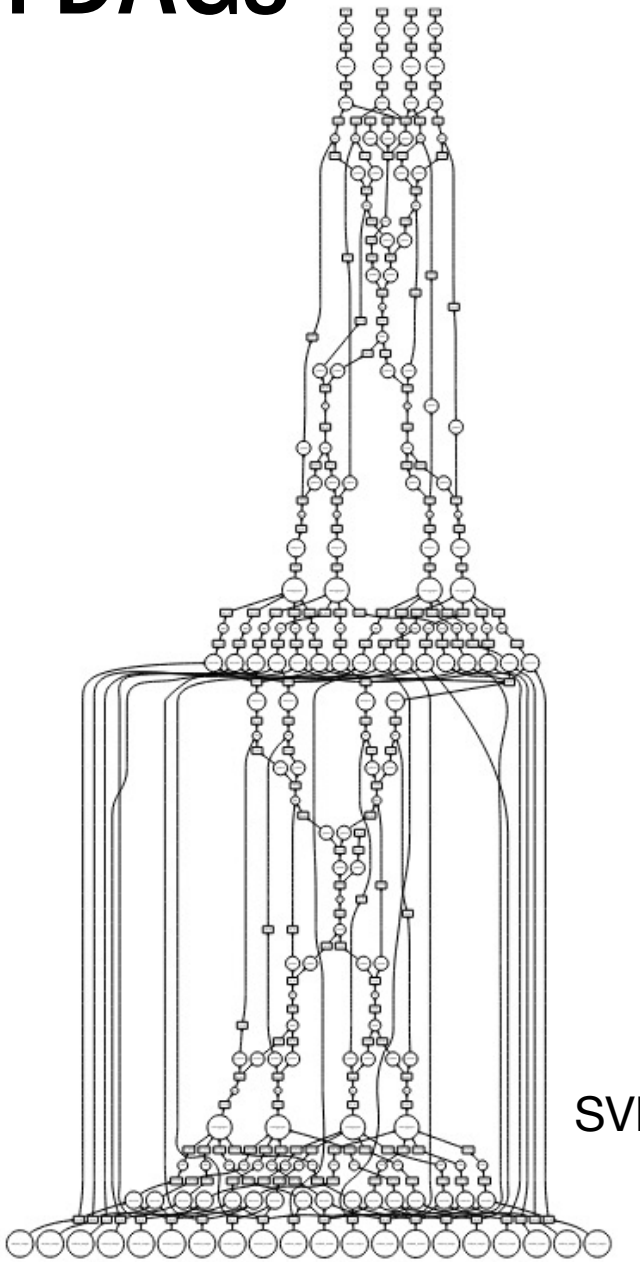
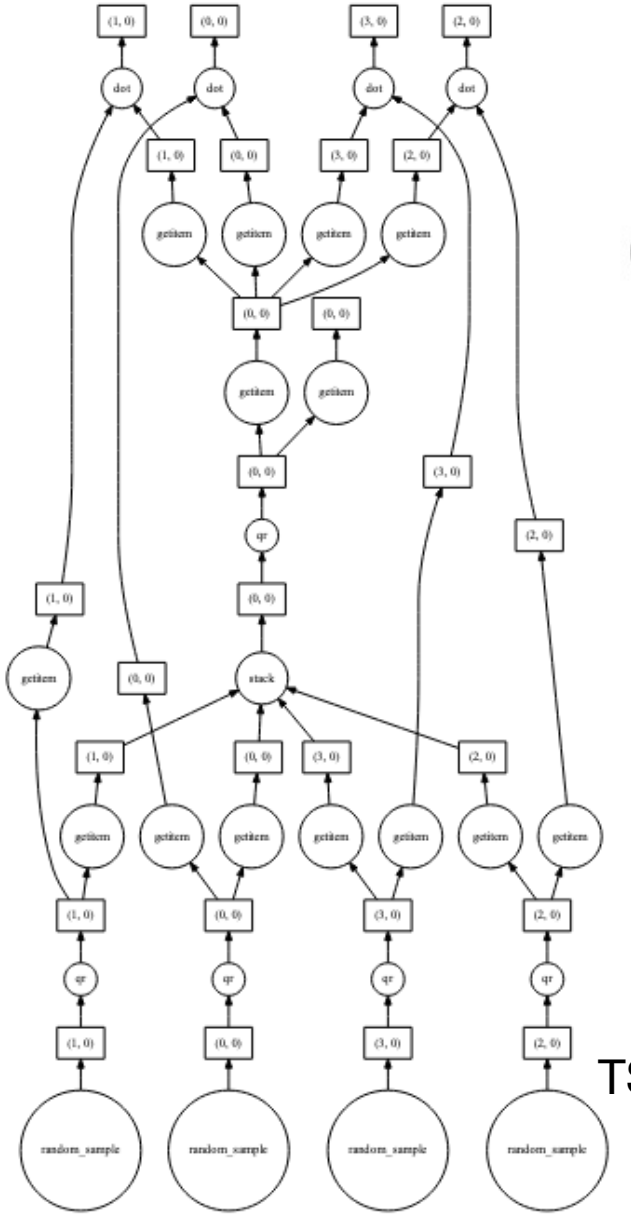
Application DAGs



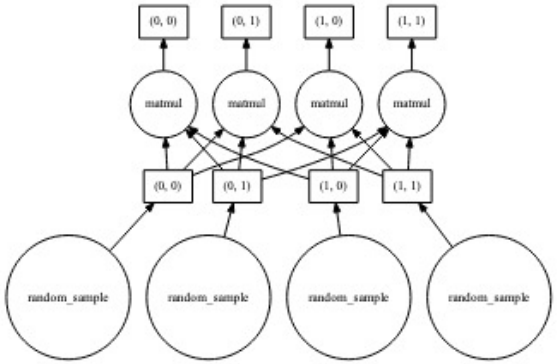
SVD1



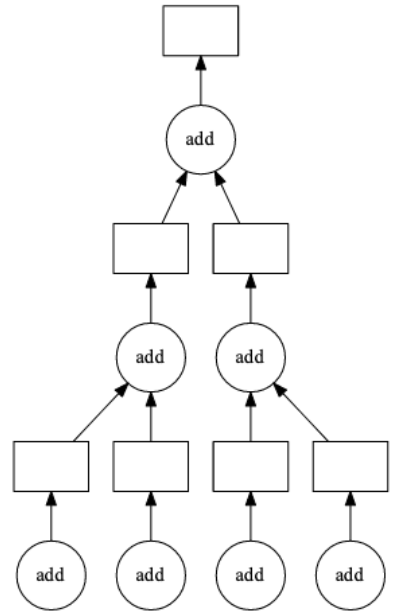
SVD2



TSQR

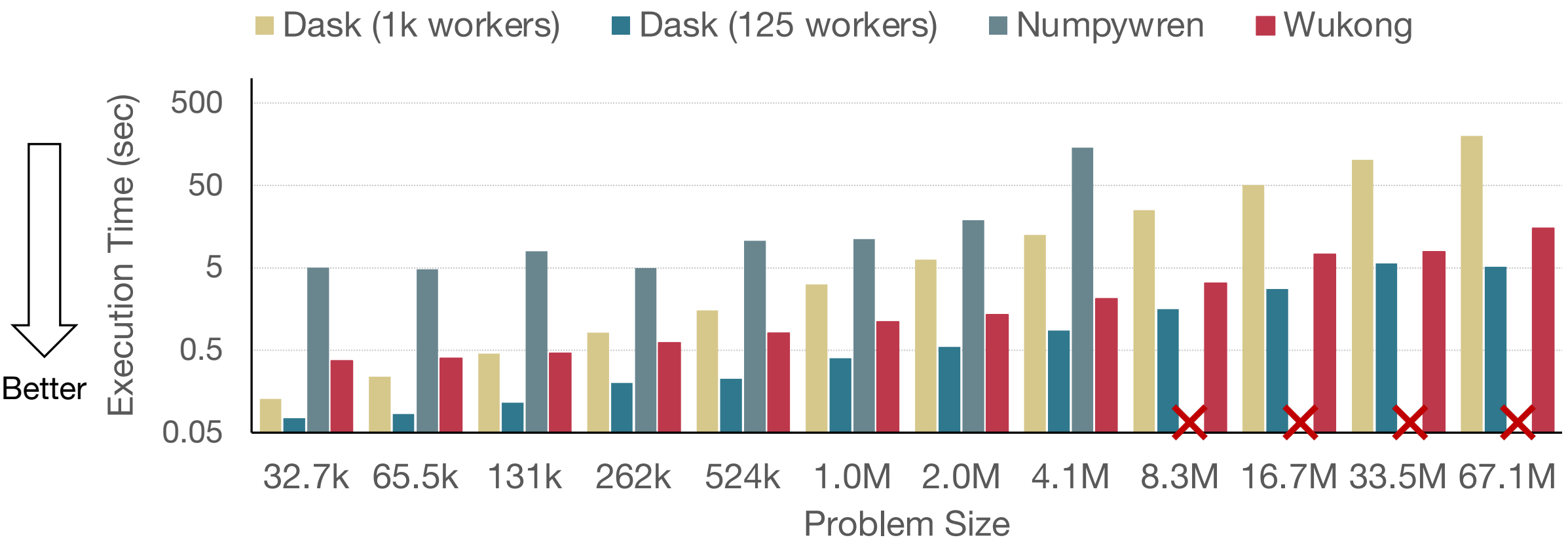


GEMM



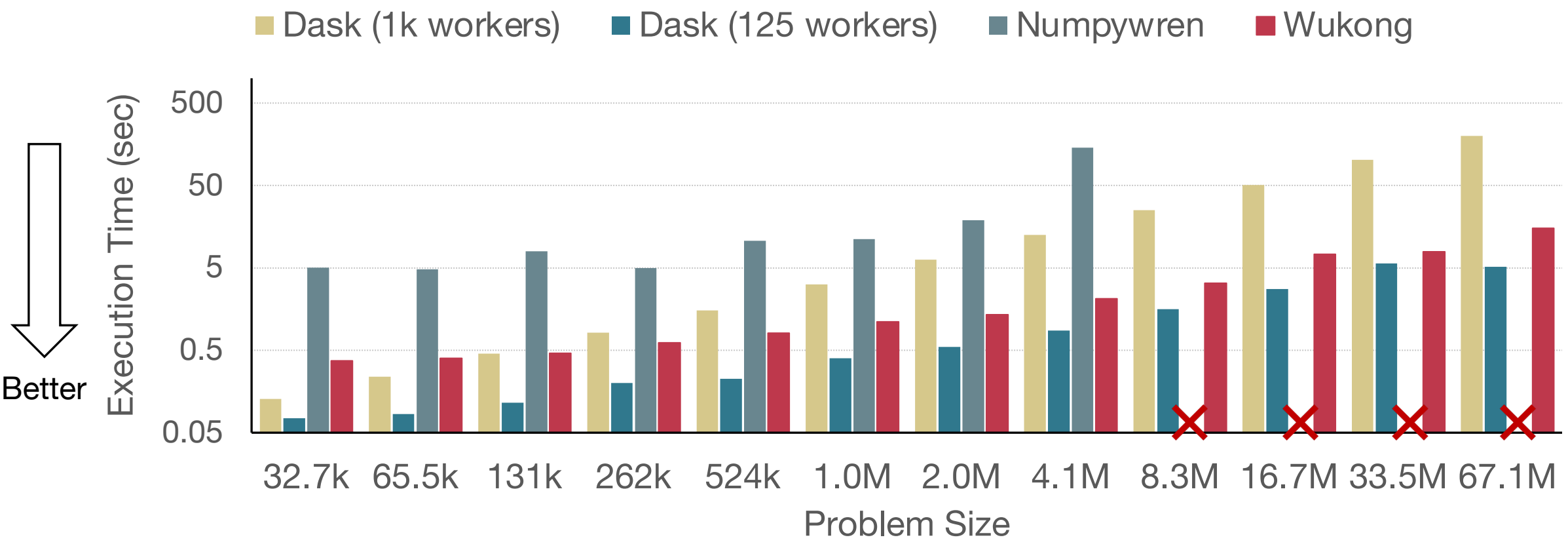
Tree reduction

Application performance: TSQR



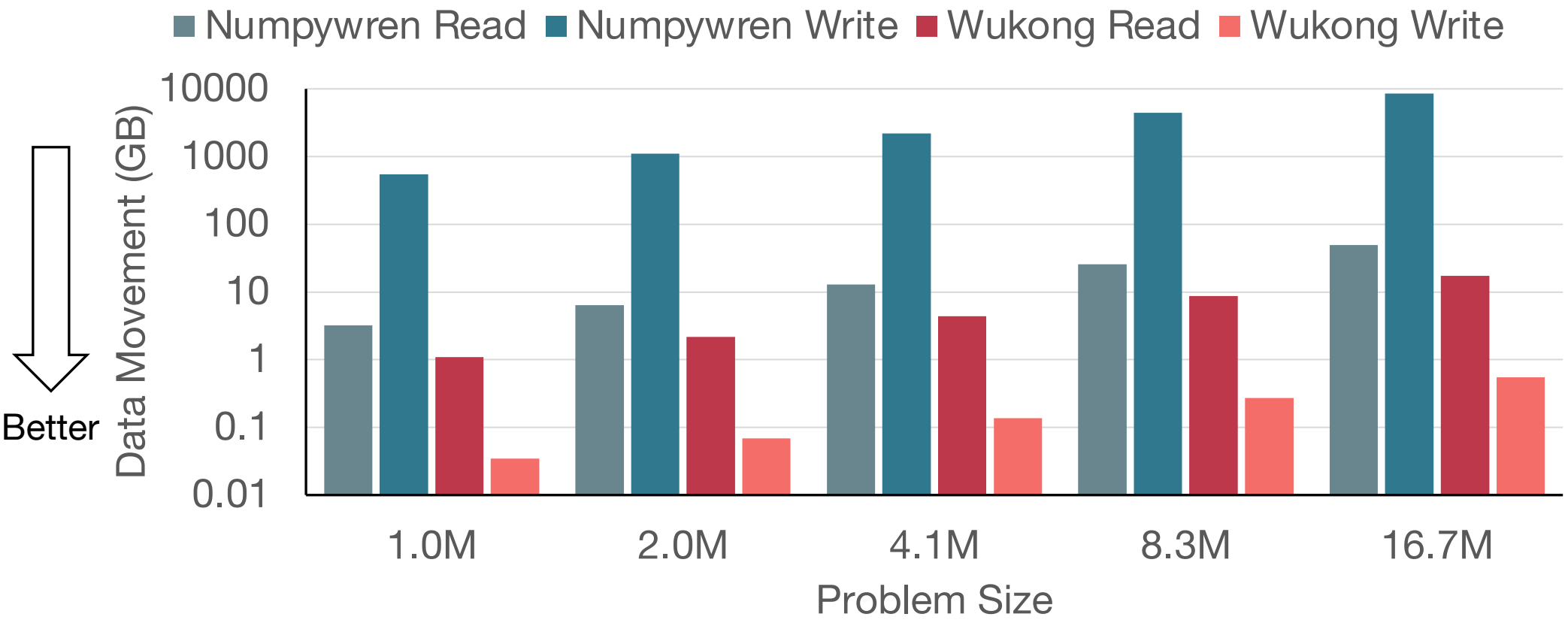
Wukong and numpywren ran on AWS Lambda w/ 3GB memory
Dask distributed ran on 125 c5.4xlarge EC2 VMs w/ 2,000 vCPU cores

Application performance: TSQR

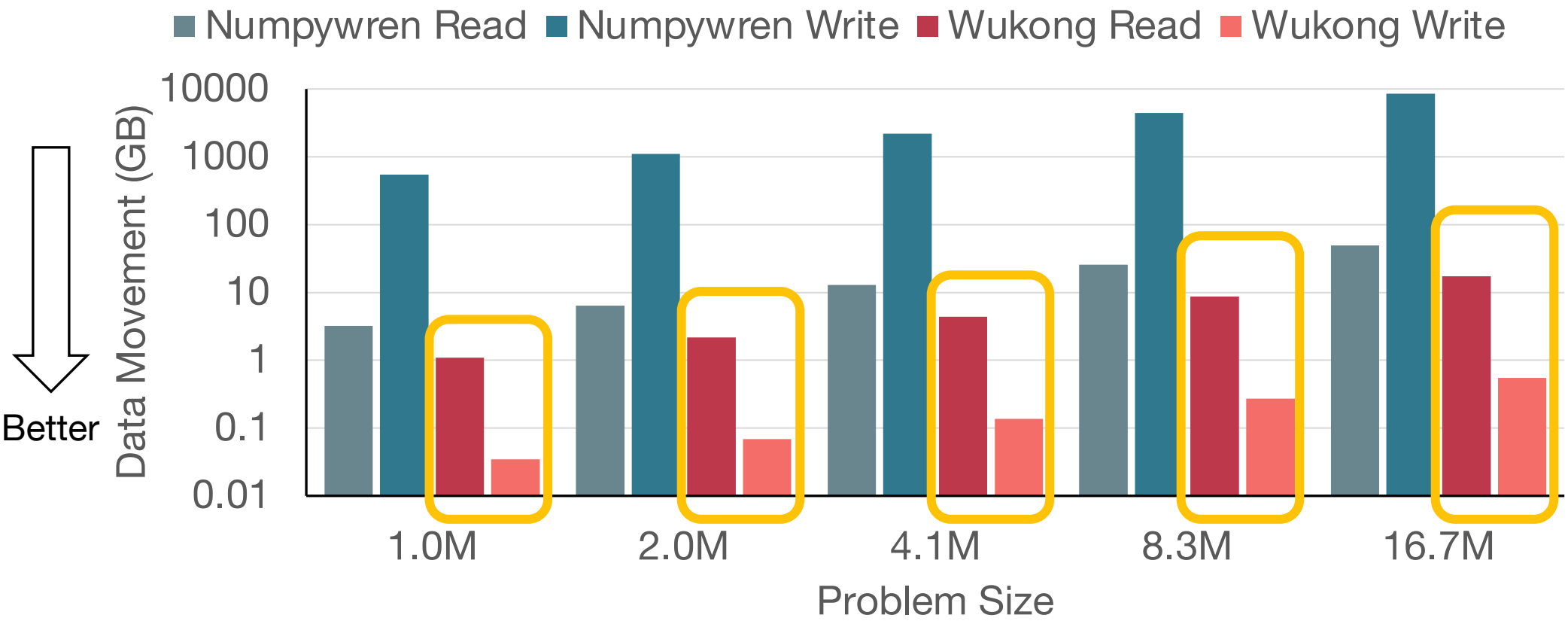


Wukong outperforms numpywren considerably for all problem sizes

Data movement cost: TSQR



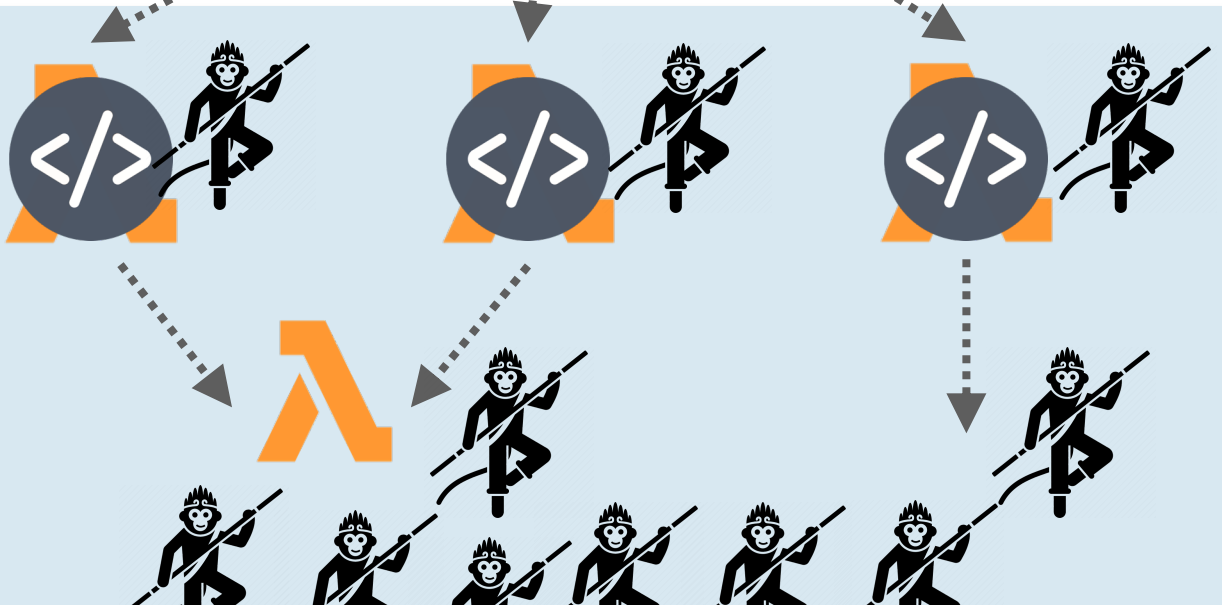
Data movement cost: TSQR



Wukong reads and writes considerably less data than numpywren

Backup slides

Wukong's magic hairs vs. decentralized scheduling



Wukong performance

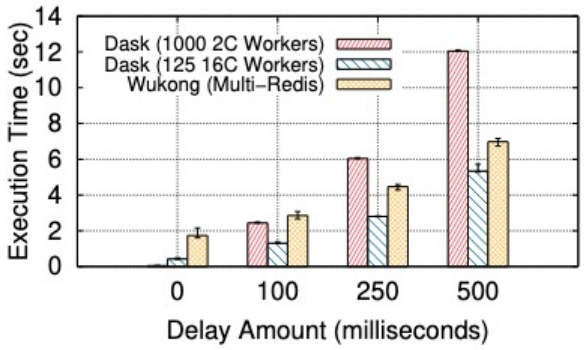


Figure 9: TR.

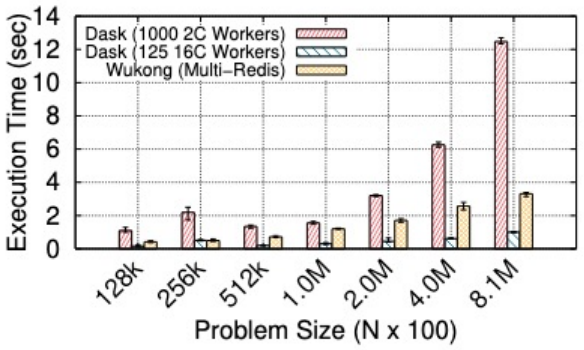


Figure 10: SVD1.

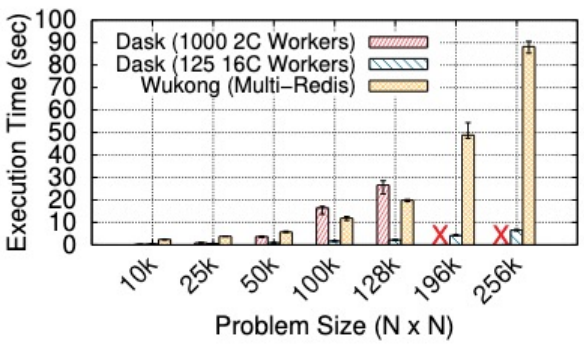


Figure 11: SVD2.

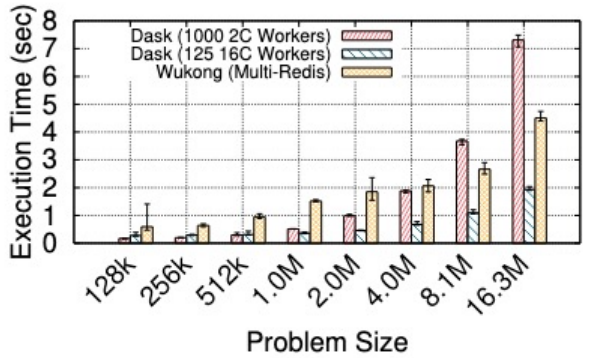


Figure 12: SVC.

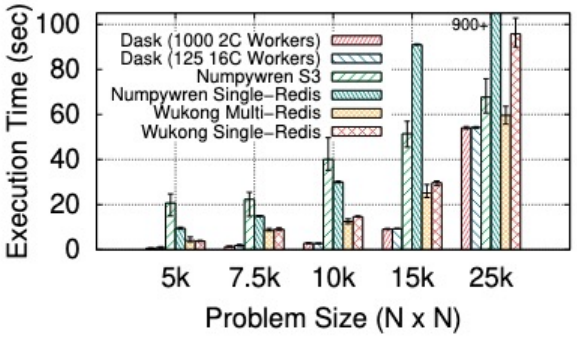


Figure 13: GEMM.

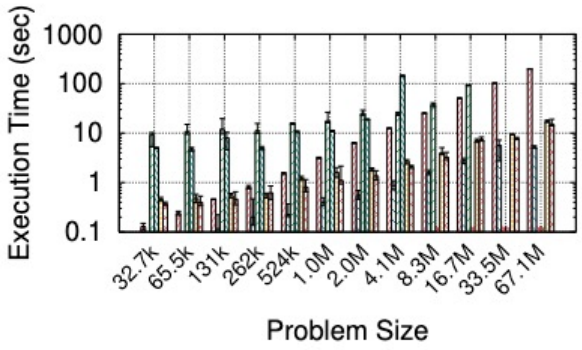


Figure 14: TSQR (log-scale).

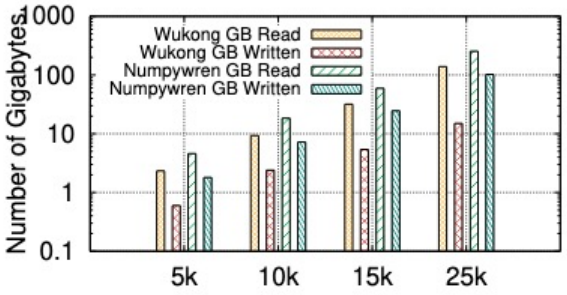


Figure 15: GEMM I/O (log).

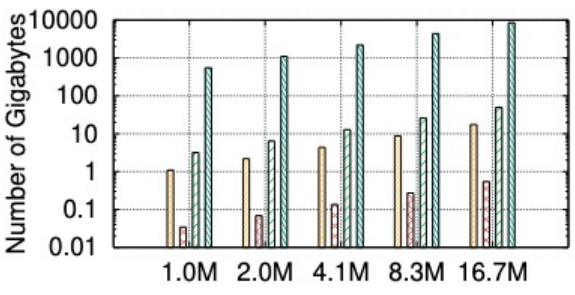
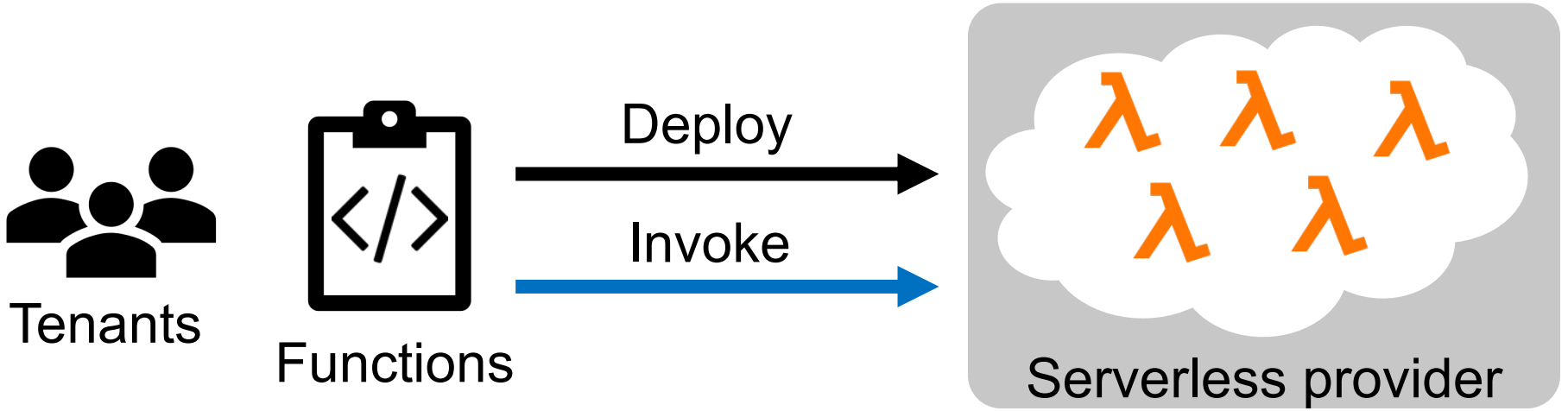


Figure 16: TSQR I/O (log).

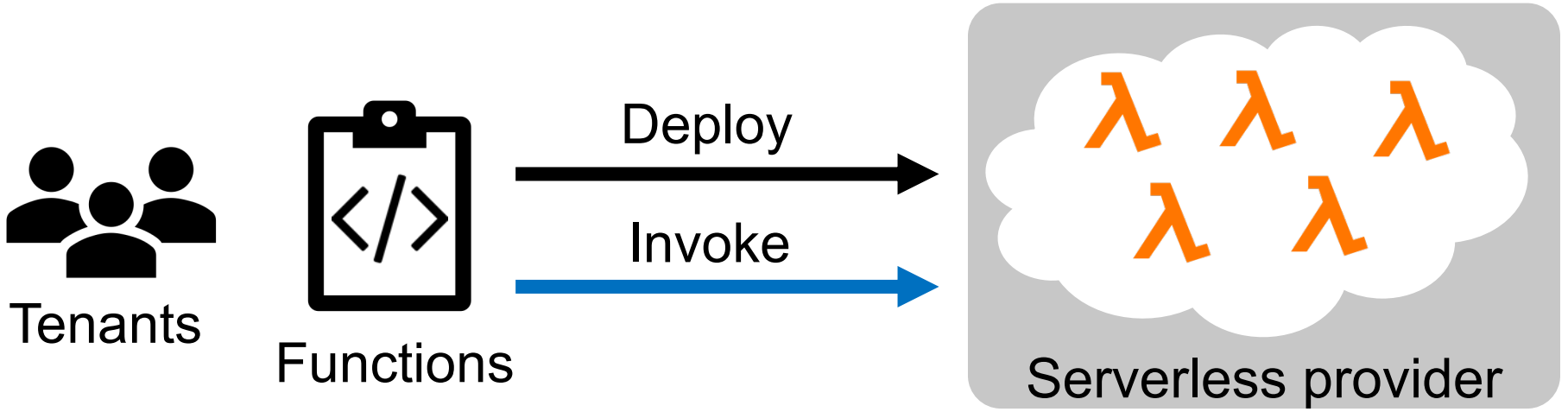
A primer on Serverless Computing

- Serverless computing enables cloud tenants to launch short-lived tasks (i.e., Lambda functions) with high elasticity and fine-grained resource billing



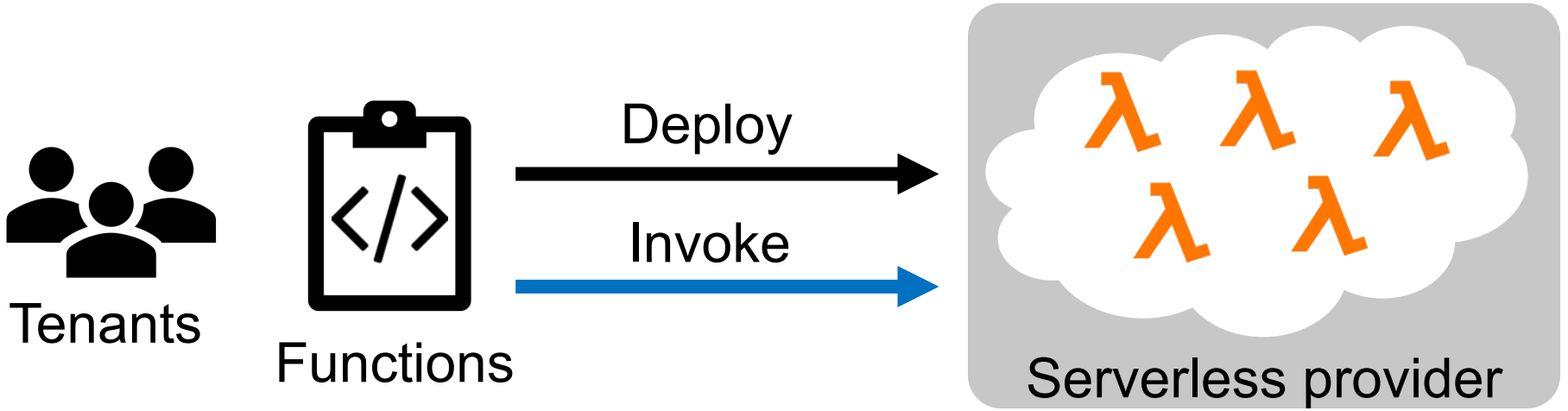
A primer on Serverless Computing

- Serverless computing enables cloud tenants to launch short-lived tasks (i.e., Lambda functions) with high elasticity and fine-grained resource billing
- Function: basic unit of deployment. Application consists of multiple serverless functions

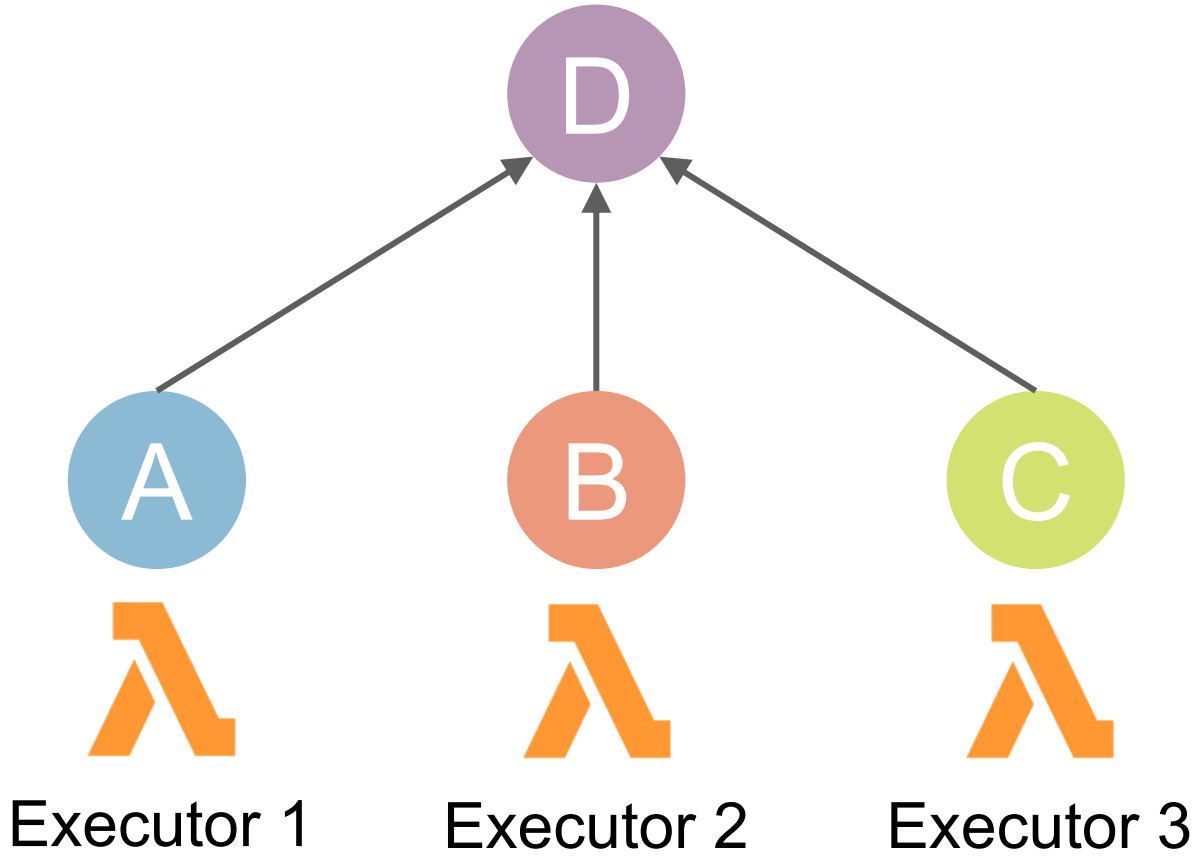


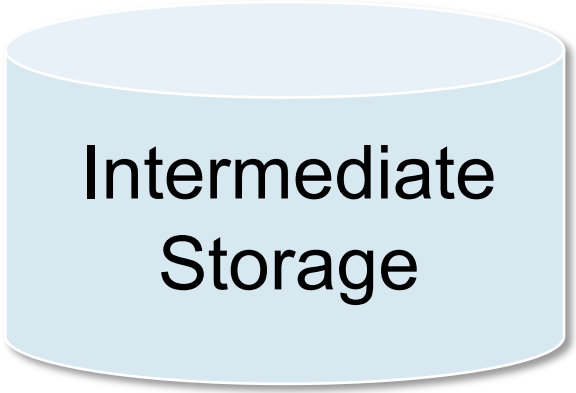
A primer on Serverless Computing

- Serverless computing enables cloud tenants to launch short-lived tasks (i.e., Lambda functions) with high elasticity and fine-grained resource billing
- Function: basic unit of deployment. Application consists of multiple serverless functions
- Popular use cases: Backend APIs, data processing…



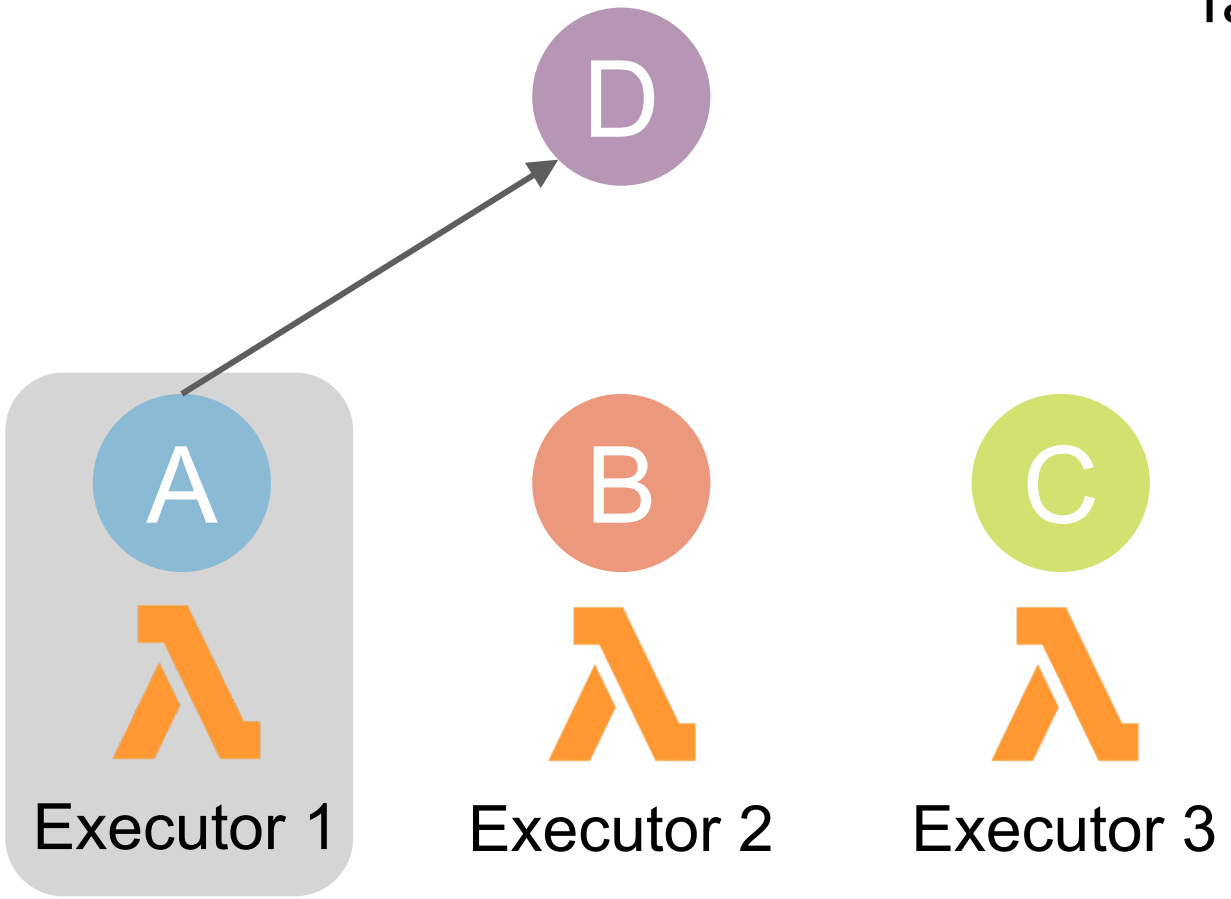
Handling fan-in



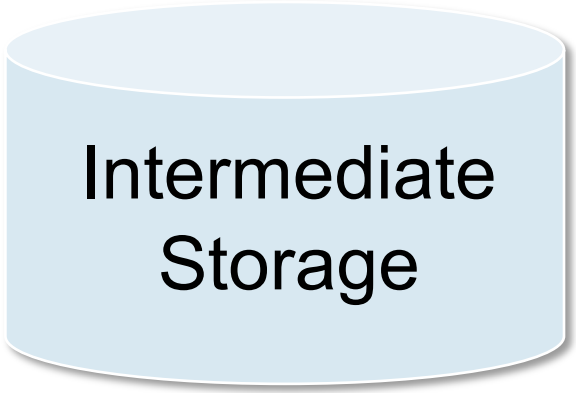


Handling fan-in

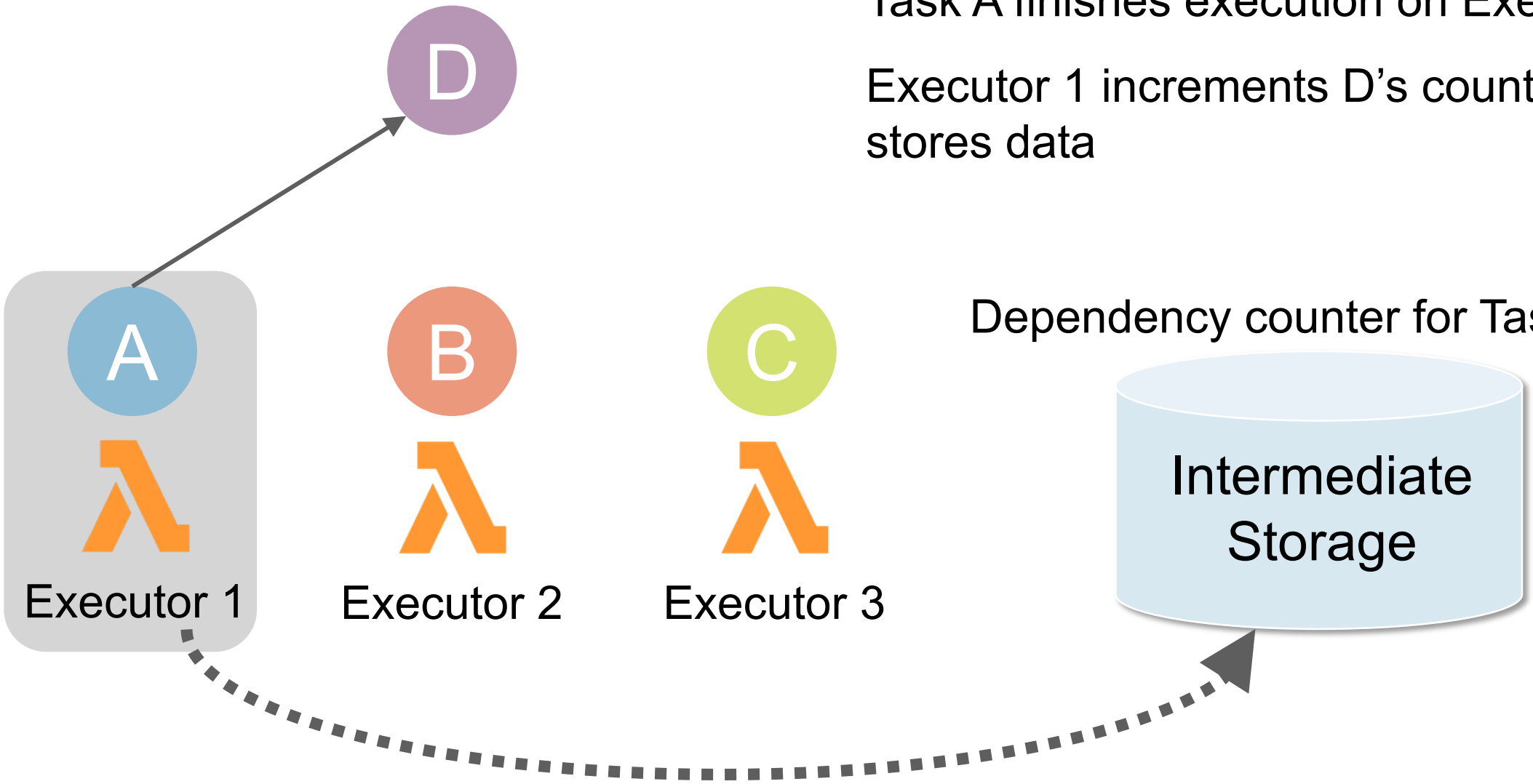
Task A finishes execution on Executor 1



Dependency counter for Task D: 0



Handling fan-in



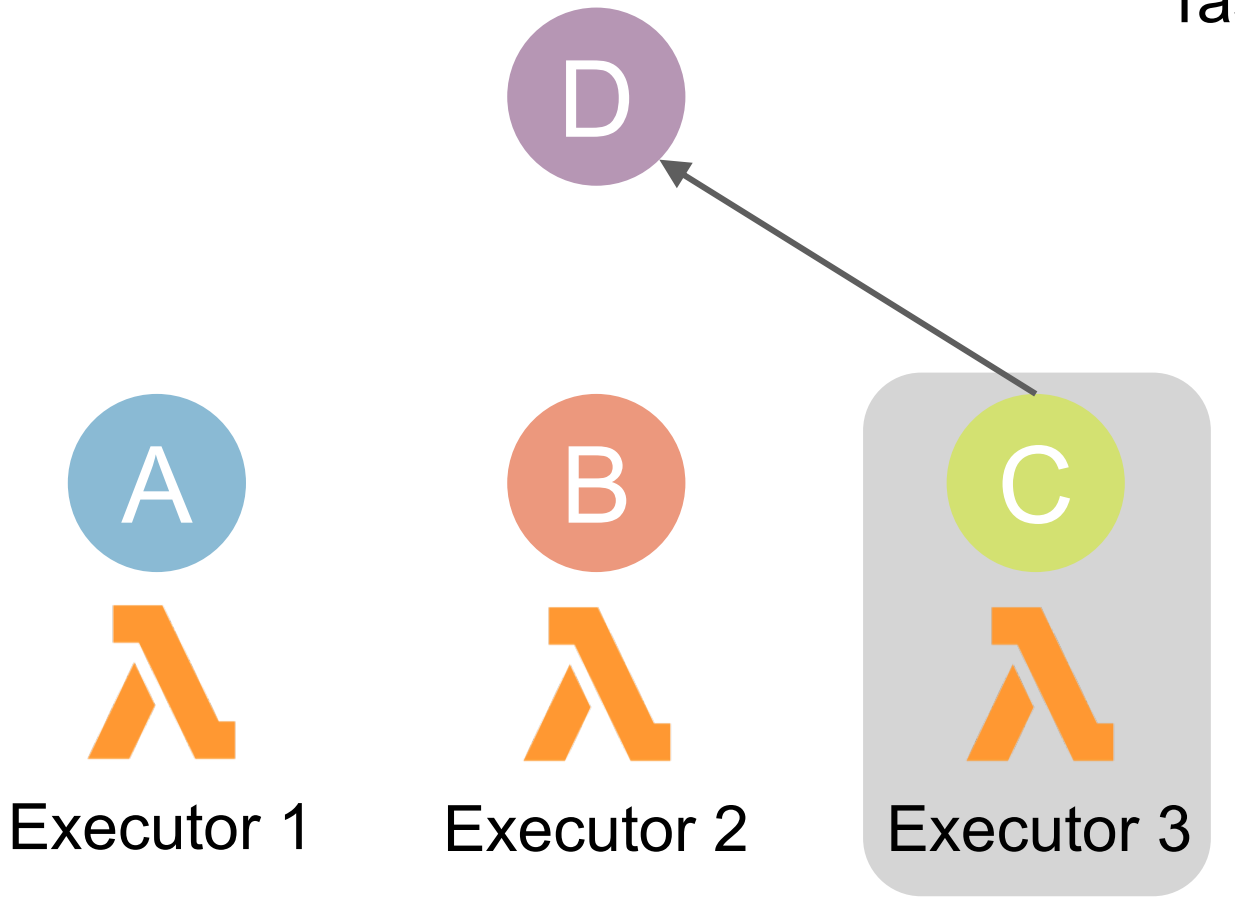
Task A finishes execution on Executor 1

Executor 1 increments D's counter and stores data

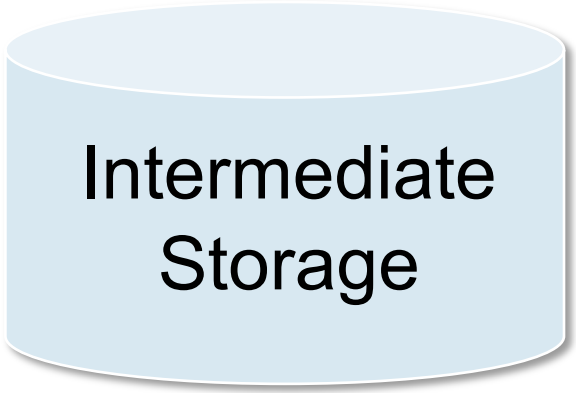
Dependency counter for Task D: **1**

Handling fan-in

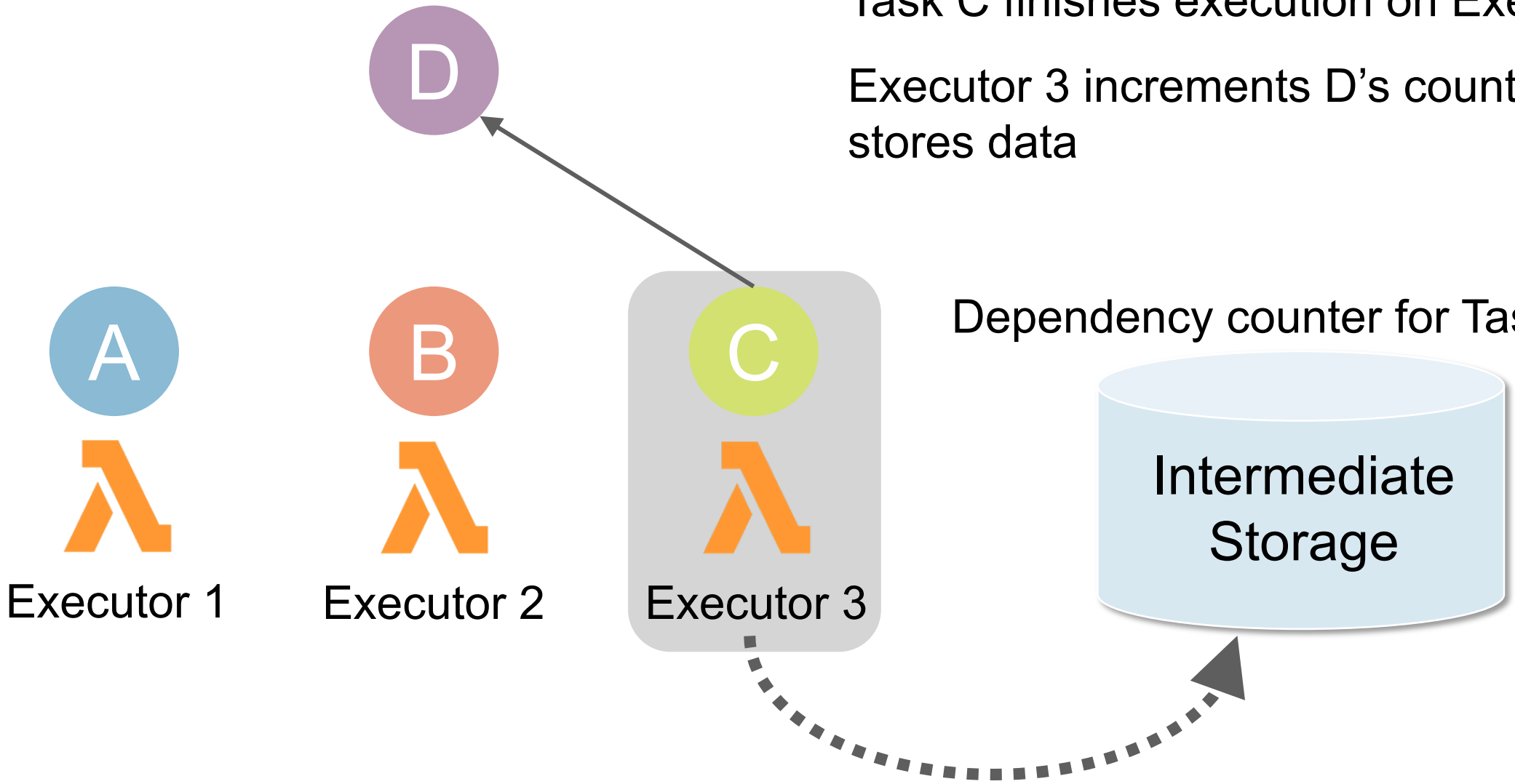
Task C finishes execution on Executor 3



Dependency counter for Task D: **1**



Handling fan-in



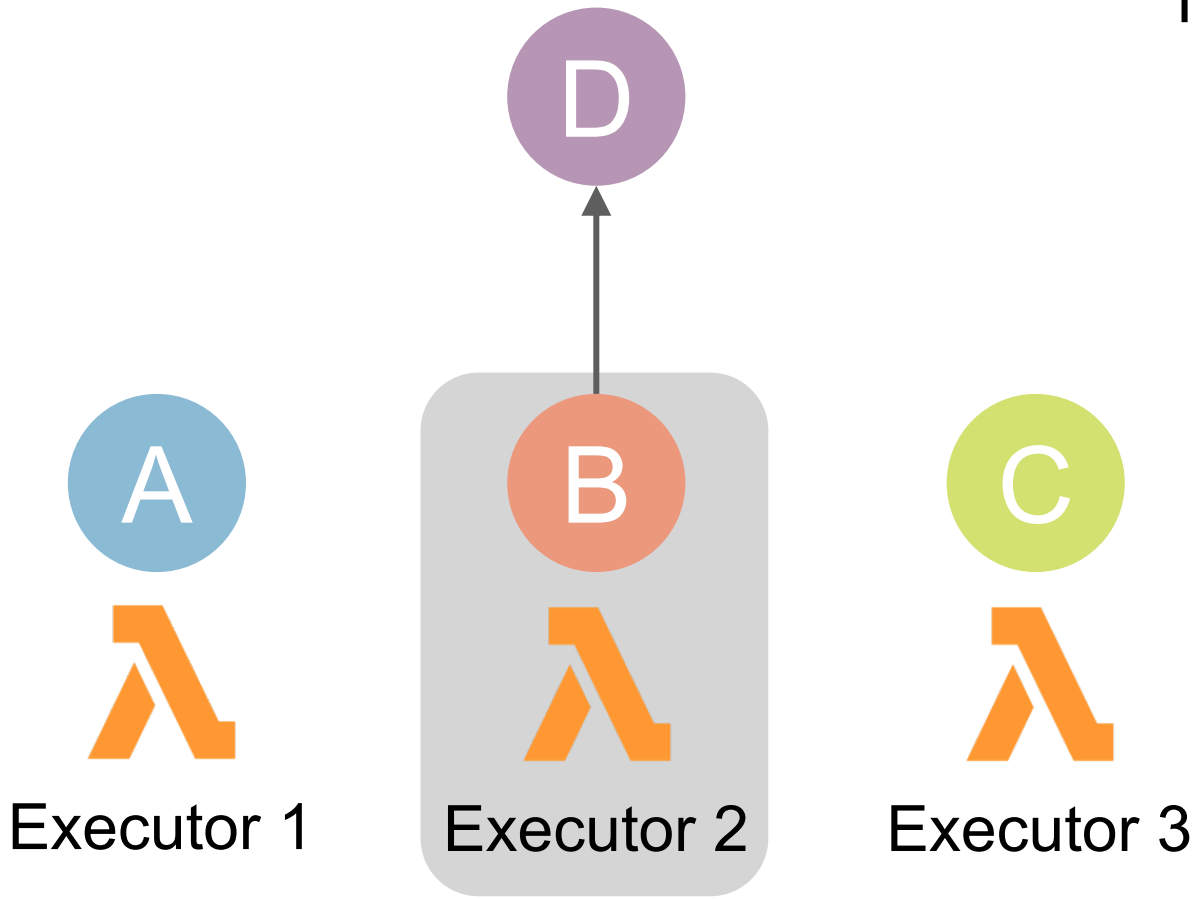
Task C finishes execution on Executor 3

Executor 3 increments D's counter and stores data

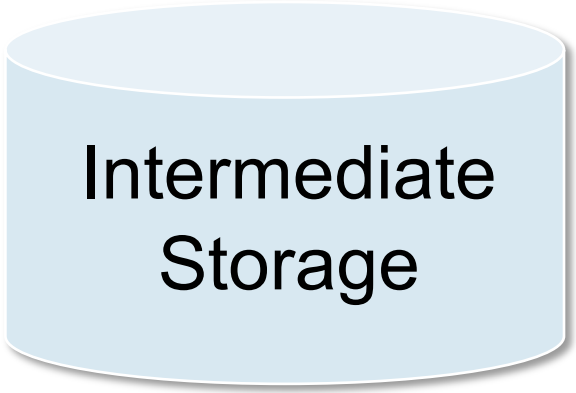
Dependency counter for Task D: **2**

Handling fan-in

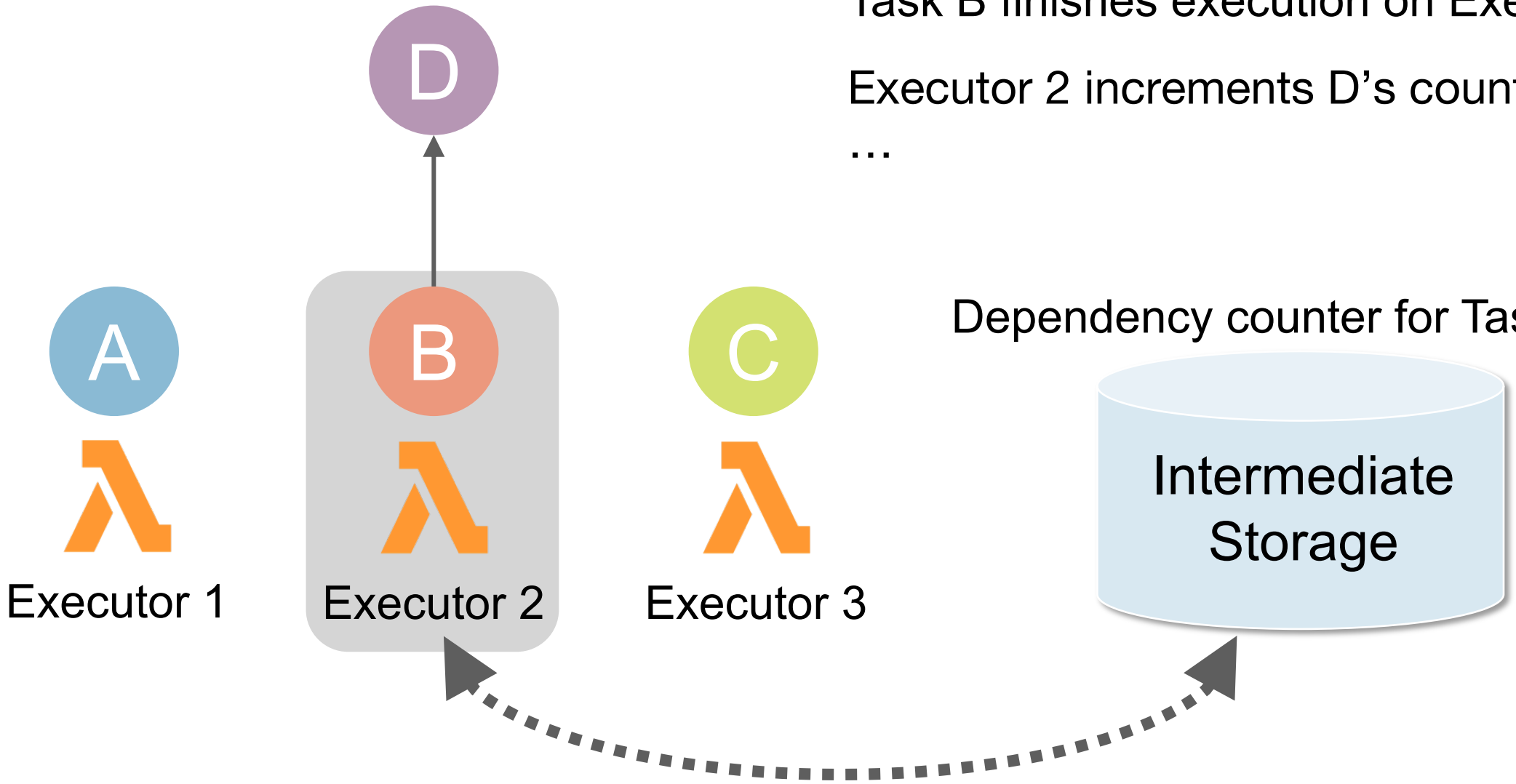
Task B finishes execution on Executor 2



Dependency counter for Task D: **2**



Handling fan-in

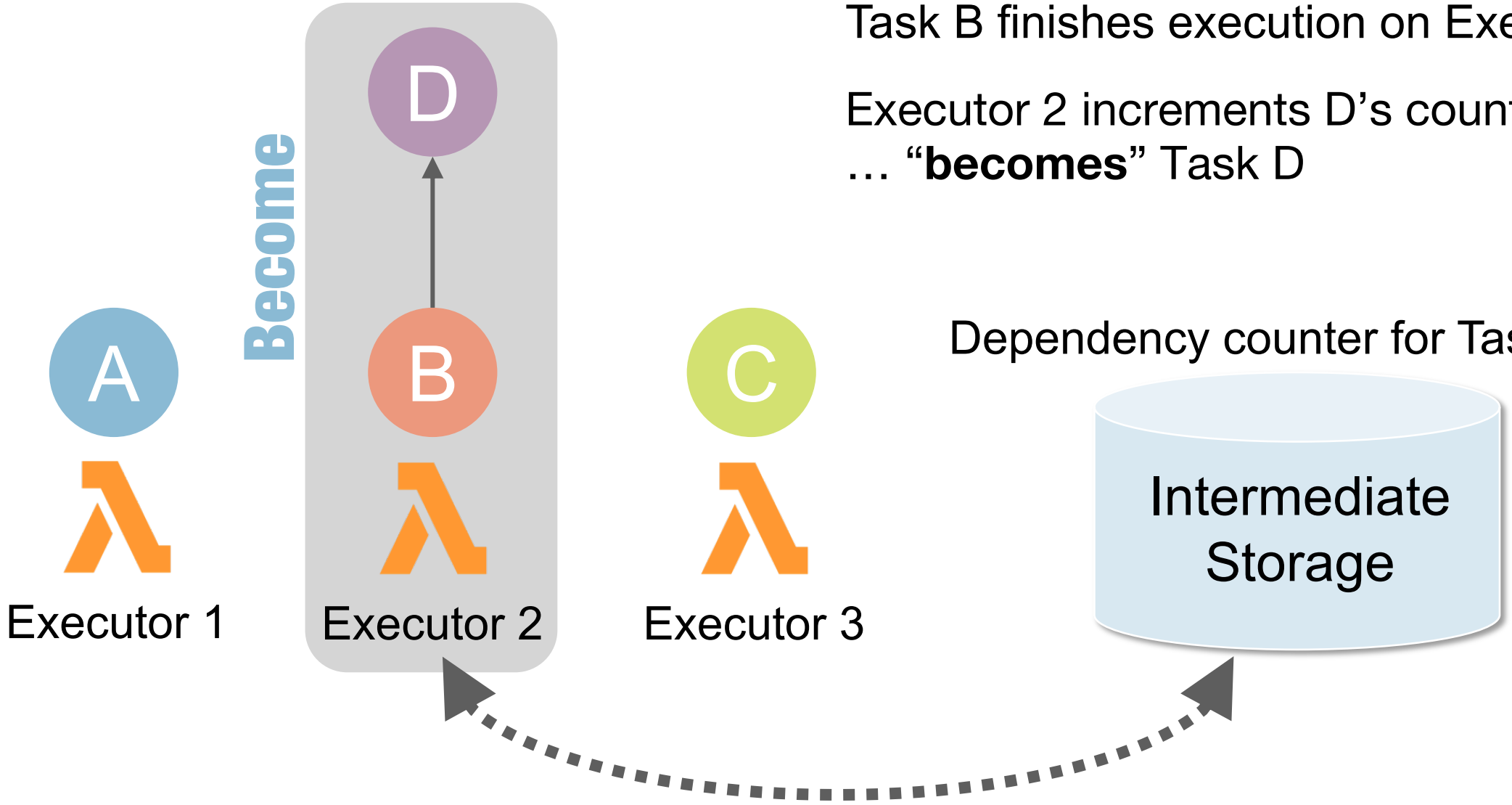


Task B finishes execution on Executor 2

Executor 2 increments D's counter and …

Dependency counter for Task D: **3**

Handling fan-in

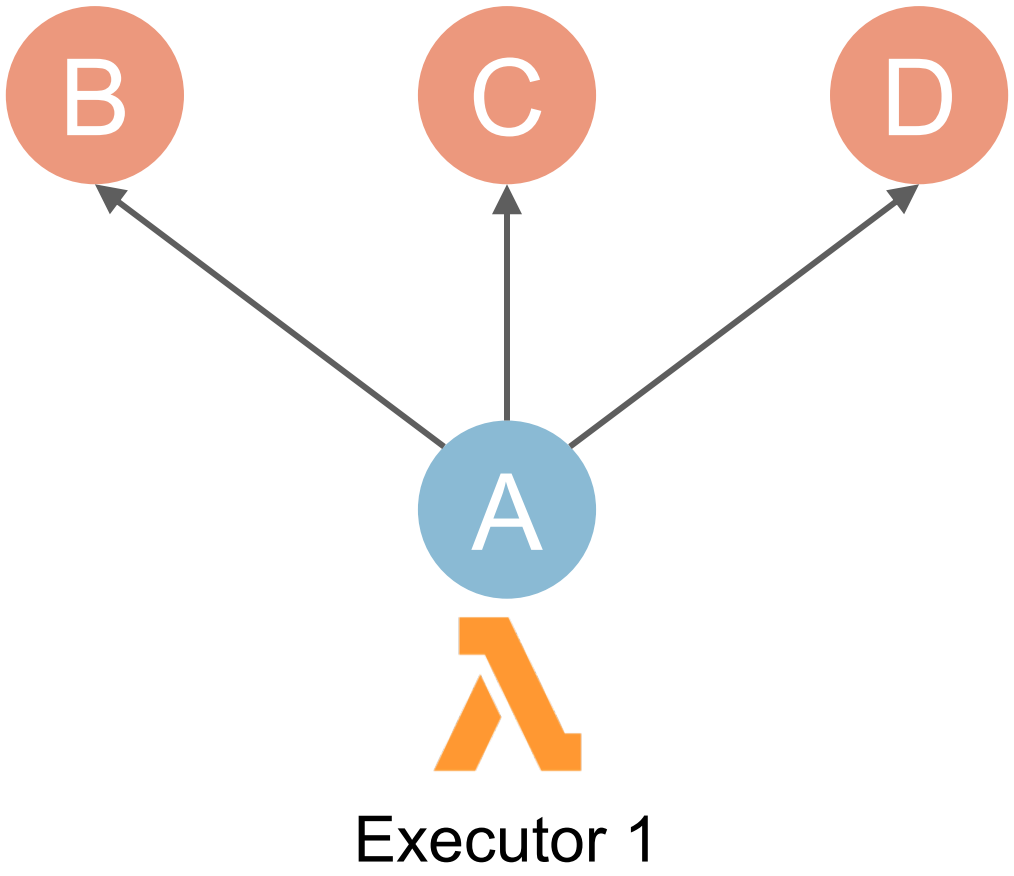


Task B finishes execution on Executor 2

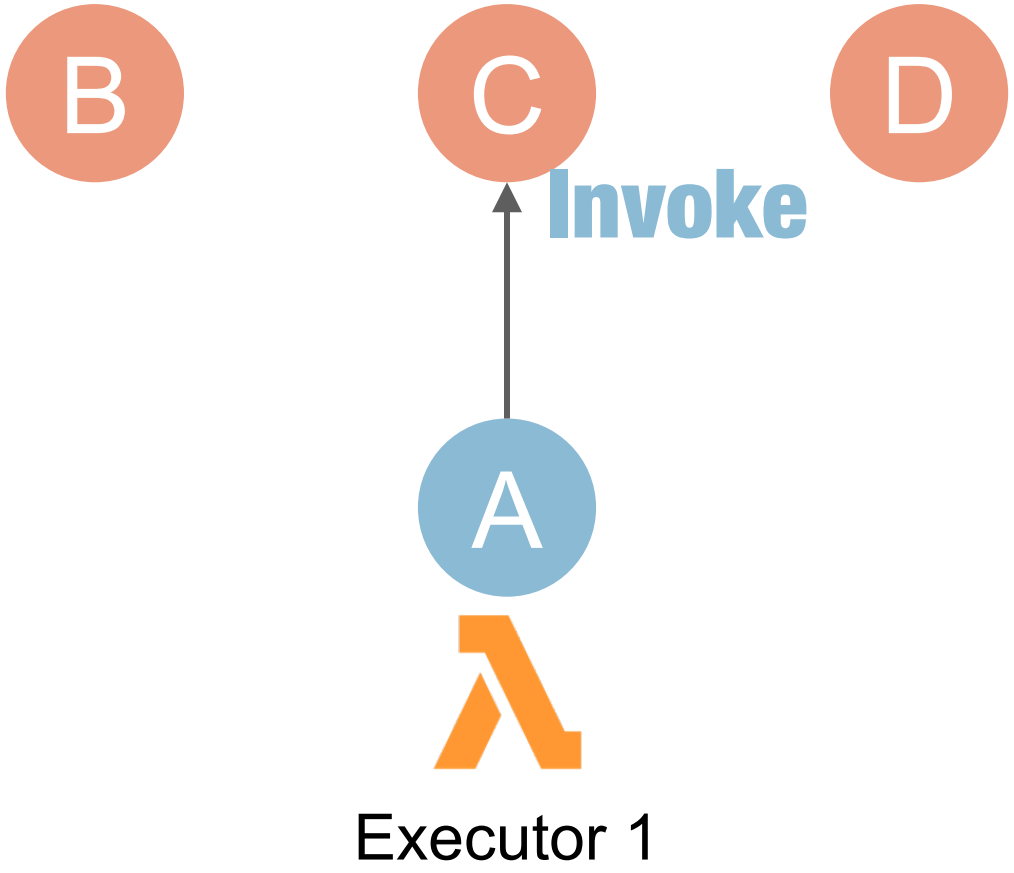
Executor 2 increments D's counter and … "**becomes**" Task D

Dependency counter for Task D: **3**

Handling fan-out



Handling fan-out



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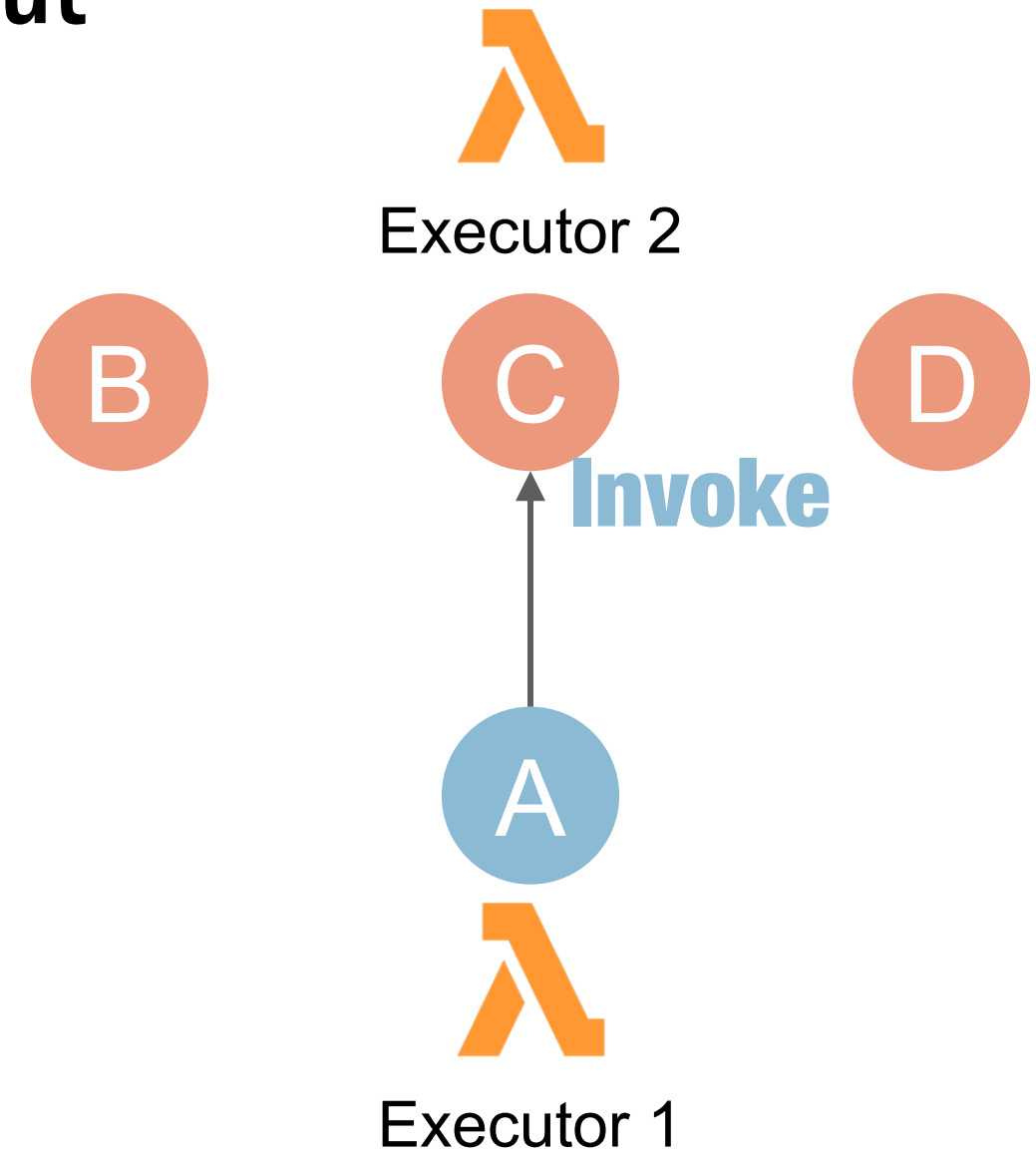
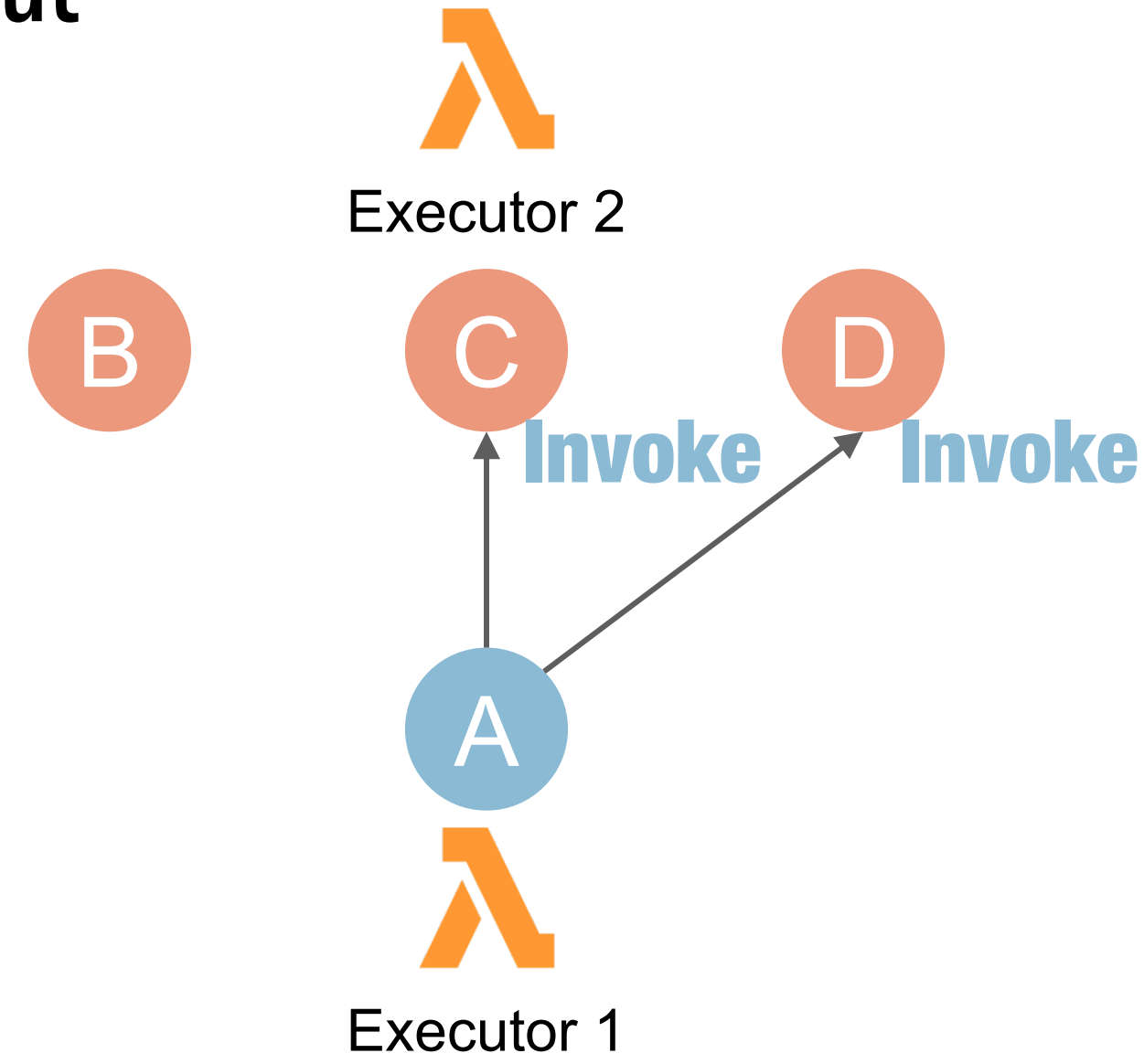
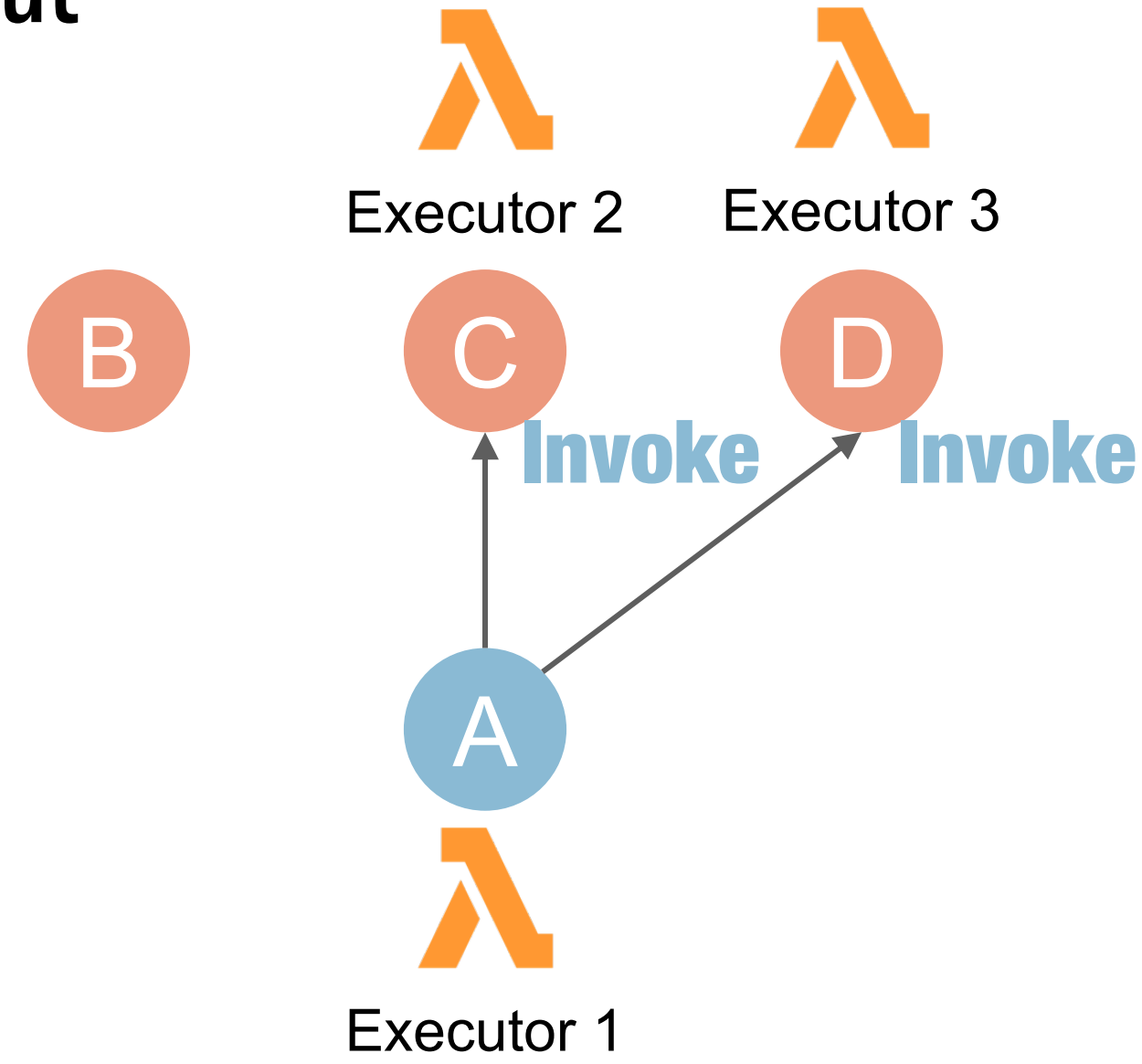


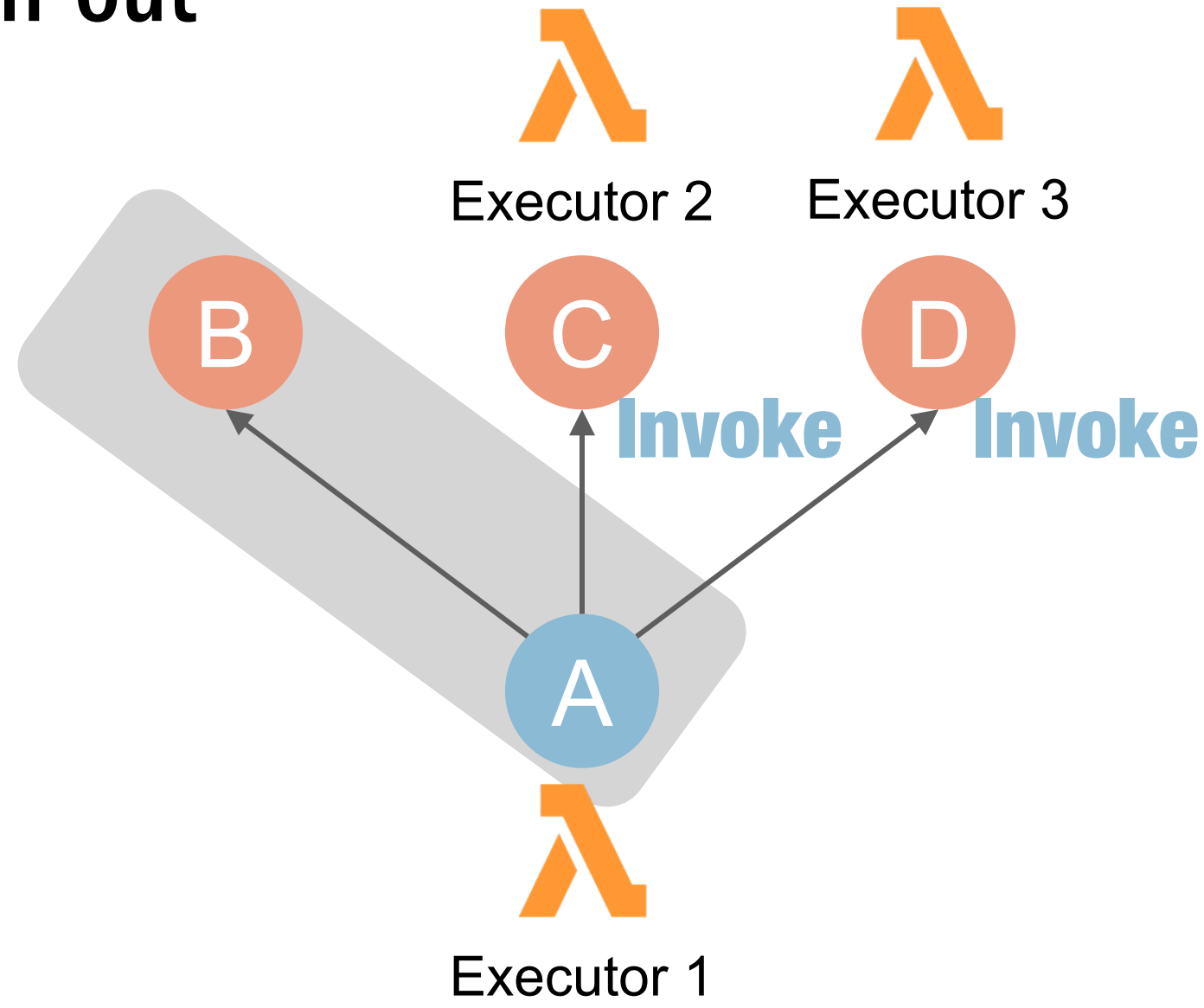
Handling fan-out



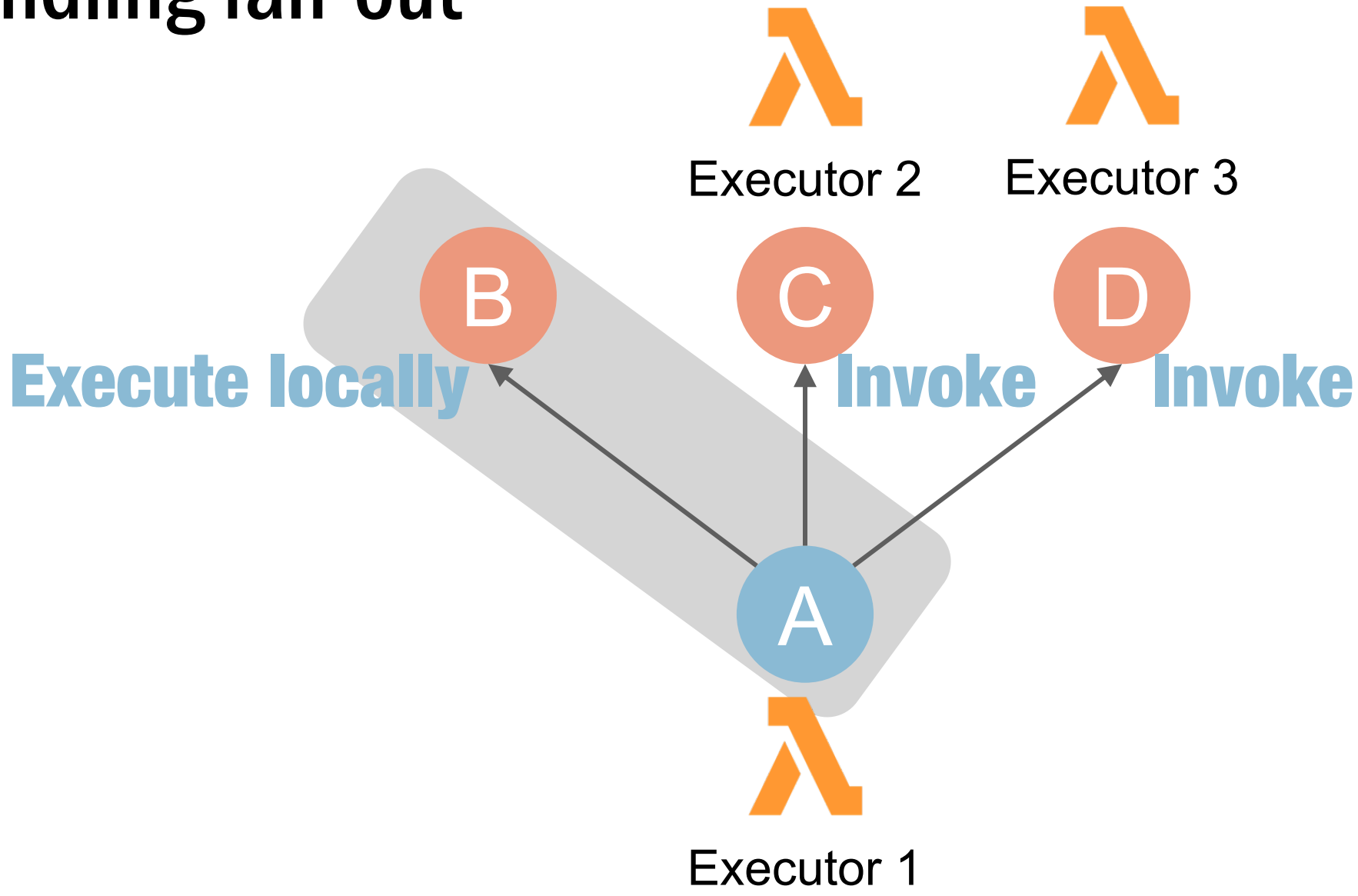
Handling fan-out



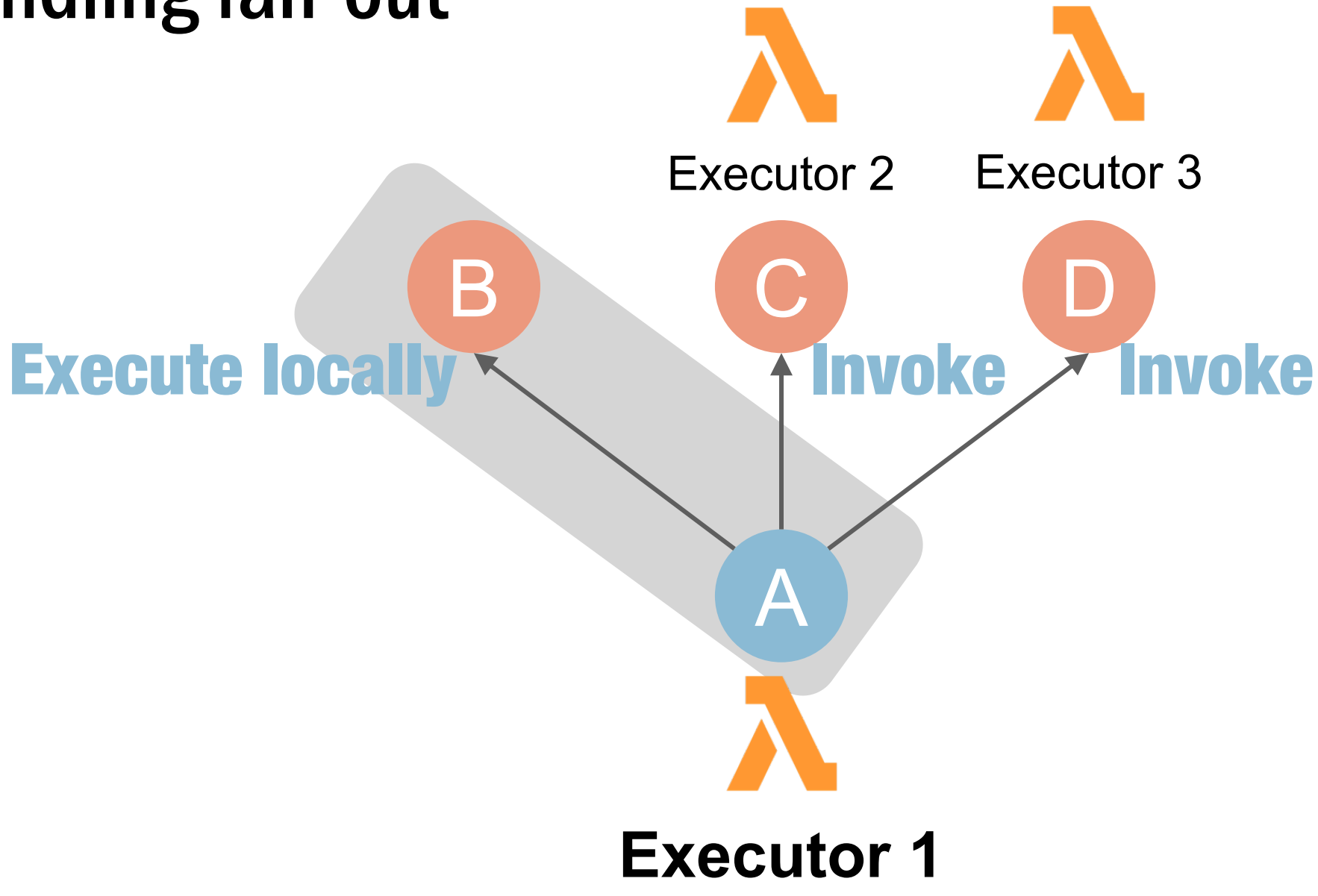
Handling fan-out



Handling fan-out

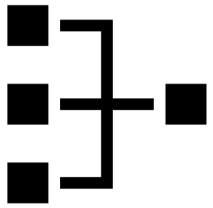


Handling fan-out



Other optimizations in Wukong

Wukong uses several techniques to enhance **data locality**



Task clustering

Eliminate intermediate data transfer by executing tasks locally

Delayed I/O

Delay performing I/O until downstream tasks are ready

Then perform task clustering on those tasks